

Mapping and Assessment of River Hydrokinetic Energy Resources across Canada and the Global Arctic

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Abstract

In remote and northern communities across Canada and the Global Arctic, reliance on imported diesel for electricity continues to pose challenges including high costs, logistical constraints, environmental degradation, and vulnerability to fuel price volatility. Hydrokinetic energy (HKE), which harnesses the kinetic energy of flowing rivers without the need for dams, offers a locally available and lower-impact renewable energy alternative. Unlike conventional hydropower, HKE can provide electricity with comparatively minimal infrastructure and ecological disturbance, making it especially suitable for sensitive and remote locations. However, the adoption of HKE has been limited by the lack of reliable data and standardized methodologies for assessing site feasibility, particularly in remote and data-scarce regions. With increasing global interest in sustainable and community-based energy transitions, there is a growing need to robustly evaluate the feasibility of HKE deployment at regional, national, and local scales.

The primary aim of this research is to increase the visibility and viability of HKE as a renewable energy solution for communities located near rivers through detailed case studies and development of validated national and regional datasets. Specifically, this research has four objectives: (1) to review and synthesize the current state of HKE assessment methodologies with a focus on localized and regional approaches; (2) develop two high-resolution, validated HKE resource databases – one for all of Canada and another for the entire Global Arctic; (3) carry out full-scale, site-specific field assessments at diverse rivers, including those in remote and Arctic locations, to test current standards and methods; and (4) assess the socioeconomic readiness and feasibility of HKE deployment, particularly in the Arctic.

To achieve these objectives, a combination of literature review, remote sensing optimization, advanced GIS analysis, field data collection, hydrodynamic modeling, and socioeconomic analysis was employed. A comprehensive review identified methodological inconsistencies in localized and regional HKE assessments, highlighting the need for standardized methods and more uniform data integration. Surface water mapping approaches were developed and tested using Sentinel-1 Synthetic Aperture Radar and Sentinel-2 Multispectral Instrument satellite imagery across diverse Canadian landscapes, applying both spectral indices and machine learning classification techniques. These data and methods were evaluated to optimize waterbody detection accuracy. The insights from this work on remotely sensed data were then applied to update and improve the national HKE database for Canada by updating measurements of river width. This was performed through integrating newly available datasets and modern computational techniques, such as cloud-based satellite image processing. Key parameters to HKE estimation, including flow, depth, width, velocity, and power, were

estimated at a notably increased spatial resolution and with a uniform methodology. This resulted in the development of the Canadian River Hydrokinetic Energy (CRHE) database, including 252,000 km of stream length. With estimates available at 1,325,261 cross sections in the database, an average spacing of 190 m between measurements was achieved. A similar approach was employed for estimating HKE resources in the Global Arctic. The updated databases for Canada and the Arctic were validated using HKE estimates derived from field measurements and hydrodynamic modeling. Field data was collected with an acoustic Doppler current profiler (ADCP) and real-time kinematic differential global positioning system (RTK-DGPS) for hydrodynamic model calibration using TELEMAC-2D software. Detailed site assessments at four rivers, including the Iqaluit Kuunga (Sylvia Grinnell) River and Rivière Rouge, evaluated flow dynamics, seasonal variability, and optimal turbine placement. Socioeconomic feasibility was examined through spatial analysis of Arctic communities, identifying 325 communities with promising HKE potential and analyzing variables such as resource proximity, local resource strength, and diesel offset potential.

The outcomes of this research include two validated, high-resolution HKE datasets – one for Canadian HKE resources and another for Global Arctic resources – that enable more accurate and accessible preliminary site identification by communities, developers, and policymakers. Remote sensing methods were optimized to produce improved estimates of river width, a critical input for HKE assessment, and practical recommendations are provided for future surface water mapping using remotely sensed data. Site-specific HKE resource assessments revealed the importance of capturing fine-scale spatial and temporal flow variations for optimal turbine placement, and demonstrated that reach-averaged velocities can significantly underestimate HKE potential. This study also offers guidance on field data collection techniques and HKE resource calculation practices. The Iqaluit Kuunga River case study confirmed the technical feasibility of HKE deployment in Arctic environments and proposed a framework for evaluating community readiness for energy transition across the Global Arctic. Collectively, the resulting datasets and recommendations lay a foundation for targeted, data-informed HKE development and support future renewable energy transitions in remote regions.

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List of Acronyms

ADCP	Acoustic Doppler current profiler
ADV	Acoustic Doppler velocimeter
AEP	Annual energy production
AMHG	At-a-many-station hydraulic geometry
ANN	Artificial neural network
ANOVA	Analysis of variance
AWEI	Automated water extraction index
AWEI_NSH	Automated water extraction index, no shadow
AWEI_SH	Automated water extraction index, shadow
AWEI_BOTH	Automated water extraction index, combined no shadow and shadow
BOA	Bottom of atmosphere
CE	Commission error
CoS	Cost of Service Model
CRHE	Canadian River Hydrokinetic Energy database
CSI	Critical success index
DDC	Depth duration curve
DEM	Digital elevation model
DHG	Downstream hydraulic geometry
DOE	Department of Energy
DSM	Digital surface model
DT	Decision tree
DTM	Digital terrain model
EO	Earth observation
EPRI	Electric Power Research Institute
ESA	European Space Agency
EW	Extra-wide swath
FDC	Flow duration curve
FPIC	Free, prior, and informed consent
FR	Fraser River
GEE	Google Earth Engine
GEM	Global Environmental Multiscale Model
GHGs	Greenhouse gases
GIS	Geographic information system
GNS	Geographic Names Server
GPS	Global positioning system
GRWL	Global River Widths from Landsat dataset
GRADES	Global Reach-scale A priori Discharge Estimates for SWOT

GRD	Ground range detected
HG	Hydraulic geometry
HKE	Hydrokinetic Energy
HRDEM	High Resolution Digital Elevation Model
IEC	International Electrotechnical Commission
IIHR	Iowa Institute of Hydraulic Research
IQR	Inter-quartile range
ISODATA	Iterative self-organizing data analysis technique
IW	Interferometric wide swath
KNN	K-nearest neighbour
LiDAR	Light detection and ranging
LULC	Land use land cover
LWIC	Land water image classification
L5TM	Landsat-5 Thematic Mapper
L7ETM	Landsat-7 Enhanced Thematic Mapper
L8OLI	Landsat-8 Operational Land Imager
MA	Matching area
MAE	Mean absolute error
MAPE	Mean absolute percent error
MBE	Multi-beam echosounder
ME	Mean error
MLC	Maximum likelihood classifier
MLR-CCA	Multiple linear regression with canonical correlation analysis
MNDWI	Modified normalized difference water index
MODIS	Moderate Resolution Imaging Spectroradiometer
MT	Manually determined optimized threshold
NASA	National Aeronautics and Space Administration
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
NHN	National Hydro Network
NIR	Near-infrared
OCRE-NRC	Ocean, Coastal and River Engineering -National Research Council
NRCan	Natural Resources Canada
NSE	Nash-Sutcliffe Efficiency
OA	Overall accuracy
OE	Omission error
OT	Otsu's threshold
OTL	Optimal turbine location
PDC	Power duration curve
RCED	Remote Community Energy Database

RE	Renewable energy
REC	Renewable energy converter
RedR	Red River
RMSE	Root-mean-square error
RRMSE	Relative root-mean-square error
RHAM	Rapid Hydropower Assessment Model
RF	Random forest
RougeR	Rivière-Rouge
RT	Random trees
RTK-DGPS	Real-time kinematic differential global positioning system
SAR	Synthetic aperture radar
SBE	Single beam echosounder
SDE	Standard deviation of error
SGR	Sylvia Grinnell River
SLC	Single look complex
SM	Stripmap swath
SNAP	SeNtinel Application Platform
SRTM	Shuttle Radar Topography Mission
SVM	Support vector machine
SWAT	Soil and Water Assessment Tool
SWIR	Short-wave infrared
SWOT	Surface Water and Ocean Topography Mission
S1SAR	Sentinel-1 Synthetic Aperture Radar
S2MSI	Sentinel-2 Multispectral Instrument
TOA	Top of atmosphere
USGS	United States Geological Survey
VDC	Velocity duration curve
WRI	Water ratio index
WSC	Water Survey of Canada
WSC-MD	Water Survey of Canada Measurement Database

List of Symbols

a	Calibration coefficient for hydraulic geometry derived width [-]
a_{ma}	Calibration exponent for estimation of Q_{ma} from e [-]
A	River cross-sectional area [m ²]
A_d	Drainage area [km ²]
α	Adjustment parameter for the turbinable flow curve [-]
b_{ma}	Calibration exponent for estimation of Q_{ma} from A_d [-]
b	Calibration exponent for hydraulic geometry derived width [-]
B_i	Width on the power duration curve that the point represents as a decimal probability [-]
β_T	Coefficient in the turbinable flow curve [-]
c_{ma}	Calibration exponent for estimation of Q_{ma} from P_{ma} [-]
c	Calibration coefficient for hydraulic geometry derived depth [-]
C	Adjustment parameter for the turbinable flow curve [-]
C_p	Coefficient of power [-]
d	River depth [m]
d_{ma}	Calibration exponent for estimation of Q_{ma} from T_{ma} [-]
$d(f_Q)$	Depth as a function of flow frequency [m]
γ	Specific weight of water [kg m ⁻² s ⁻²]
γ_T	Coefficient in the turbinable flow curve [-]
e	The base of natural logarithms [-]
f	Calibration exponent for hydraulic geometry derived depth [-]
f_Q	Flow frequency corresponding to a flow on a flow duration curve [-]
FP	False positive [-]
FN	False negative [-]
g	Number of monthly mean widths [-]
h	Number of satellite-based width measurements for an open water month [-]
H	Hydraulic head [m]
k	Calibration coefficient for hydraulic geometry derived velocity [-]
k_M	Unit conversion factor for Manning's equation [-]
κ	Kappa coefficient [-]
κ_T	Coefficient in the turbinable flow curve [-]
L	Length of river segment [m]
μ	Monthly mean width [m]
μ_i	Monthly weighted temporal mean width [m]
m	Calibration exponent for hydraulic geometry derived velocity [-]
n_M	Manning's roughness [s m ^{-1/3}]

N	Number of samples [-]
N_B	Number of points on the power duration curve [-]
N_h	Number of hours of turbine operation in a year [hours year ⁻¹]
OA	Overall accuracy [-]
P_H	Hydropower [kg m ² s ⁻³]
P_i	Theoretical power present at the point on the power duration curve [kg m s ⁻³]
P_K	Hydrokinetic power [kg m ² s ⁻³]
P_{ma}	Mean annual precipitation [mm year ⁻¹]
Q	Discharge [m ³ s ⁻¹]
Q_D	Design discharge [m ³ s ⁻¹]
$Q(f_Q)$	Discharge as a function of flow frequency [m ³ s ⁻¹]
Q_{ma}	Mean annual discharge [m ³ s ⁻¹]
Q_T	Turbinable flow [m s ⁻³]
ρ	Density of water [kg m ⁻³]
ρ_{blue}	Reflectance value of the blue band of imagery [-]
ρ_{green}	Reflectance value of the green band of imagery [-]
ρ_{NIR}	Reflectance value of the near infrared band of imagery [-]
ρ_{SWIR1}	Reflectance value of the first shortwave infrared band of imagery [-]
ρ_{SWIR2}	Reflectance value of the second shortwave infrared band of imagery [-]
R	Hydraulic radius [m]
R^2	Coefficient of determination [-]
S	Slope [-]
S^2	Variance [m s ⁻¹]
TN	True negative [-]
TP	True positive [-]
T_{ma}	Mean annual temperature multiplied by a factor of ten [°F]
θ	Adjustment parameter for the turbinable flow curve [-]
v	River velocity [m s ⁻¹]
v_{pi}	Observed depth-averaged velocities in the point surveys [m s ⁻¹]
w	River width [m]
$w(f_Q)$	Width as a function of flow frequency [m]
ϕ_T	Coefficient in the turbinable flow curve [-]
X	Correct predictions by the model, hits, or matching area [km ²]
Y	Overpredictions by the model, false alarms, or commission error [km ²]
Z	Underpredictions by the model, misses, or omission error [km ²]
Z_T	Adjustment parameter for the turbinable flow curve [-]

Validation/measured value [-]
Ensemble mean [-]

Chapter 1. Introduction

1.1 Background and Motivation

Hydrokinetic energy (HKE) may prove to be a technically feasible and socially relevant source of renewable energy for suitable communities and regions. In particular, it is likely to be a promising solution for remote communities currently reliant on diesel for electricity that are also near river sites with appropriate hydraulic conditions. In Canada and other countries with widely dispersed northern communities, diesel is imported for electricity by ship, plane, or seasonal ground transportation, and communities are not connected to a larger, stable regional or national electrical grid (Agu et al., 2023; de Witt et al., 2021). This practice impedes community innovation, drives high electricity prices (contributing to poorer economic conditions for locals), and contributes to environmental degradation both locally (through black carbon deposits and poor air quality) and globally (Gritsenko and Salonen, 2021; Kholod et al., 2016; Weis et al., 2008). Additionally, interviews with communities in Nunavut, Canada revealed great interest for transitioning to renewable energy (Nunavut Arctic College, 2024). HKE, and renewable energy in general, presents an exciting opportunity for communities to explore community-based electricity generation as opposed to corporation-based electricity generation, where social and location-specific nuances can be included in energy system design (Hoicka et al., 2021; McMaster et al., 2024).

The feasibility of river HKE depends on hydraulic conditions that enable effective turbine performance and economic viability. In general, the velocity of water in the river must exceed 1.0 m/s, a typical turbine cut-in velocity, for most flow conditions and must be below 3.5 m/s, a typical turbine cut-out velocity, for most flow conditions (McCallum et al., 2021; ORPC, 2023). The second most important consideration is the water depth. Most turbines require at least 3 meters of water depth to operate, but some require more than 10 meters (Kirke, 2024). Some other location-specific considerations are proximity to communities for transmission lines, ice and debris, and logistical challenges (Kirby et al., 2023a).

River site identification and investigation is therefore an important step before deploying HKE technology. This process typically takes place in three steps: (1) initial site identification and reconnaissance, (2) rough estimation of HKE resource using remote methods, and (3) river site HKE estimation using field data collection, hydrodynamic modelling, and hydrological modelling if required. The last step, providing an accurate estimate of the HKE resource, is the most costly and time-consuming, and yet it is the most important to properly size equipment and determine deployment strategies. The

current literature describing examples of step 3 river site HKE estimation is marked by inconsistencies in temporal and spatial resolution of estimation, and although standards exist for this step of HKE estimation from the International Electrotechnical Commission (IEC, 2019), they have not been tested before. Steps 1 and 2 should be completed before Step 3 to screen for site feasibility prior to undertaking a full investigation. Therefore, these steps 1 and 2 must provide suitable and actionable information. In the current literature, rough estimation of HKE resources at a large spatial scale for site identification has been limited by spatial resolution and accuracy of the estimates, making them appropriate for generalized analysis of HKE in a regional or national context, but less suitable for site identification.

Site-specific estimations of HKE are more prevalent in literature than large-scale (regional or national) estimations of HKE, but some drawbacks exist in the currently published methods. Energy availability varies seasonally and interannually in response to changes in discharge and climatic conditions. Many of the current published methods did not take into account seasonal variation of flow (Filizola et al., 2015; Kalnacs et al., 2014; Montoya Ramírez et al., 2016; Petrie et al., 2014) or considered a minimum, mean, and maximum flow condition (Holanda et al., 2017). The IEC (2019) standards for river HKE resource estimation recommend using a 15-point flow duration curve (FDC) to represent the seasonality of flow and to generate the curve with at least ten years of measured data or simulated data with less than 10% error. To develop a velocity duration curve from the FDC to estimate HKE, either five velocity-discharge measurements are needed or this data can be simulated using field measurements from three different flow conditions and less than 10% model error. These standards were not considered in earlier literature (Kasman et al., 2019; Nordino, 2016) and have not previously been tested. Additionally, spatial considerations within the river reach location have not been considered previously, namely how the velocity flow field can change between flow conditions and the resulting implication for turbine placement. Thus, this work will explore not only the standards for river HKE estimation and provide recommendations, but will also determine if flow conditions can have an impact on ideal turbine placement within a river reach.

To aid in discovering promising locations of high HKE resources for further, site-specific analysis, regional, national, and/or global estimation and accurate mapping of river HKE resources is essential. Previous literature performing such analyses has been limited by the data and methods available at the time. The first large-scale estimation of river HKE was limited to the largest rivers in Canada with 20 years or more of hydrometric measurements, and there is limited information on how this assessment was performed (UMA Group, 1980). There have subsequently been a handful of assessments with similar goals, utilizing regression models (Acres Consulting Services Limited, 1984; Jenkinson and Bomhof, 2014; Miller et al., 1986; U.S. Department of Energy, 2004),

rainfall-runoff-routing approaches with an assumed channel shape (Jacobson, 2012; Kerr Wood Leidal Associates, 2008), and hydraulic geometry (Jakimavičius et al., 2014; Jenkinson and Bomhof, 2014; Ridgill et al., 2022). The advantages of these approaches are that they can provide good estimates of regional trends of HKE resources; however, to be able to identify river sites promising for HKE extraction for further investigation, the results must be mapped to a localized-scale or cross-section-scale (meter-scale), rather than a reach-scale (kilometer-scale). Recent advances in the availability of high-resolution remotely sensed data (ESA, 2024; ESA, TAS Team, 2021) and methods of processing large amounts of spatial data, such as cloud computation (Yang et al., 2020) and advanced GIS techniques, provide promising technologies to improve the accuracy and resolution of river HKE estimates.

By leveraging these advanced techniques, more accurate and higher resolution estimates of river HKE can be developed at a large spatial (national and global) scale. However, on top of the theoretical analysis of river HKE estimates, technical and practical analysis of the resource, as described by the IEC standards (2019), can be conducted to make the mapped HKE results actionable to communities, developers, and policymakers. Theoretical resource assessment relates to evaluating the resource in an idealized situation where other factors are not considered other than the resource itself. Technical resource assessment involves consideration of the limitations of energy extraction technology. Practical resource assessment includes real-world societal, environmental, and economic constraints related to energy extraction, distribution, and use (IEC, 2011). This type of integrated and holistic analysis, incorporating all three levels of resource assessment, has not been performed on this scale for HKE resources. This type of approach is useful to communities and developers, as it considers various barriers to renewable energy, providing a more accurate representation of the HKE resource that can be harnessed. Additionally, the approach is more likely to be of interest to high-level decision- and policy-makers, as it represents the big-picture of renewable energy challenges (e.g., the full extent of diesel reliance in the Arctic) and a realistic representation of HKE feasibility. This approach was applied in the Global Arctic to identify communities feasible for HKE based on both the theoretical resource and practical considerations of each community. Additionally, the socioeconomic aspect of renewable energy transitions in the Global Arctic was studied to understand current barriers and enabling conditions for energy transition.

1.2 Objectives

The objectives of this thesis were to:

- Test the standards for site-specific river HKE resource assessments while collecting validation data for large-scale HKE mapping;

- Explore and test new data and methods identified to improve large-scale estimation of river HKE; and
- Calculate, map, and validate river HKE resource estimates in Canada and the global Arctic.
- Understand the socioeconomic readiness and feasibility of HKE deployment, particularly in the Arctic, and provide general recommendations to increase development.

1.3 Scope

The scope and organization of the thesis to meet the objectives presented in Section 1.2 is presented in Figure 1-1. A critical review of the literature (Chapter 2) was conducted to evaluate current methods of site-scale and large-scale estimation techniques and standards used to assess hydrokinetic energy resources. Newly available data and techniques that could aid in the large-scale estimation of HKE resources were also identified and guided the direction of objectives 2 and 3 in Section 1.2. A case study was performed (Chapter 3) estimating the HKE resource at a specific site in order to test and evaluate methods and standards of site-scale HKE resource estimation. Both satellite data sources (Chapter 5) and methods of processing and analyzing satellite data (Chapter 4) to improve estimates of river HKE were evaluated for accuracy and applicability to measure river characteristics at a national scale. Chapter 6 presents validated estimates of river HKE for Canada and general trends of resource availability across Canada, while Chapter 7 performs this exercise across the global Arctic. Chapter 7 also presents site-specific river HKE estimation in an Arctic river to provide context for resource availability for remote communities, while also identifying remote communities in Canada and the Global Arctic with nearby promising resource availability. Finally, using a socioeconomic analysis, Chapter 7 also illustrates that renewable energy for remote communities must be approached in a socially relevant and context-specific approach.

Chapter 2 Literature review

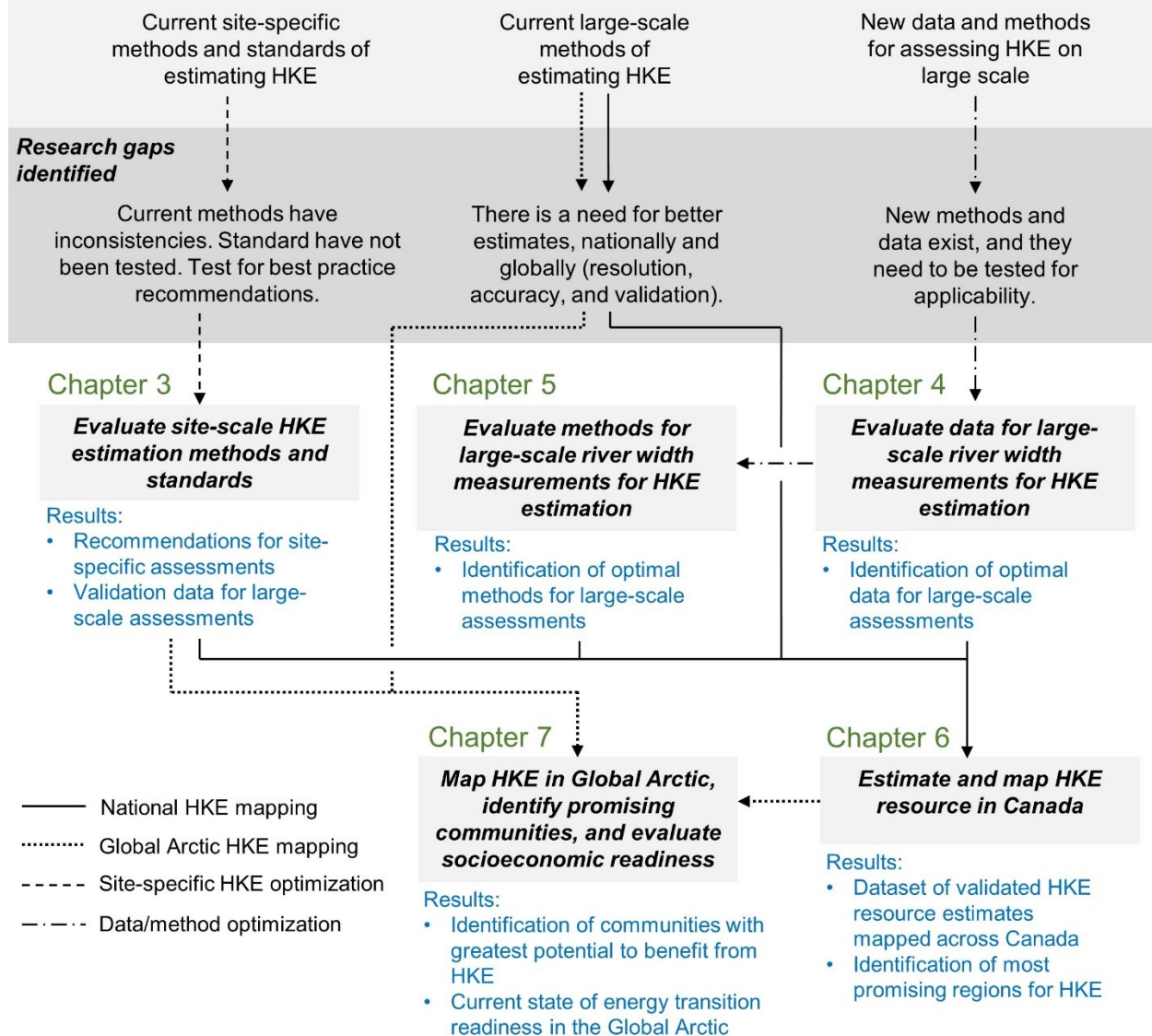


Figure 1-1: Thesis scope and outline flowchart depicting the chapters and organization of the thesis.

1.4 Equity, Diversity, and Inclusion

This research included human aspects and considerations in the study's design, execution, dissemination, and feedback. Thus, equity, diversity, and inclusion (EDI) were carefully considered in the portions of the study that were conducted in First Nations and Inuit communities and lands. Site-specific HKE studies were performed at Sagamok First Nation, Ontario, Canada and at Iqaluit, Nunavut, Canada. EDI recommendations from four resources were considered to perform the study in accordance with best practices and were regarded thoroughly when building the methodology. Namely, considerations

from **(1)** the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (Government of Canada, 2019), in particular Chapter 9: Research Involving the First Nations, Inuit and Métis Peoples of Canada, **(2)** *Negotiating Research Relationships with Inuit Communities: A Guide for Researchers* (Inuit Tapiriit Kanatami and Nunavut Research Institute, 2006), **(3)** the specific Inuit Quajimajatuqangit (traditional knowledge, values, and practices) of the researched community (Pedersen et al., 2020), and **(4)** others' experiences conducting research in the Arctic (Held, 2020; Pearce, 2021).

Emphasis was placed on informing and consulting directly with the communities well in advance of the project start date to understand how local involvement could be utilized to facilitate capacity sharing, to address community concerns, and to request feedback on the proposed methodology. During information gathering stage, fair and adequate compensation was provided, and the same value was assigned to local expertise as that assigned to peer-reviewed scientific knowledge. Prior to any field data collection, permission was granted to the research team to be present in the field study locations, and considerations of the impact of the research on the community and area were considered thoroughly. The extent of the granted permission was different depending on the location.

Using the various resources that exist to aid researchers, research in First Nations and Inuit communities was performed ethically so that relationships were built in good faith (Government of Canada, 2019; Held, 2020; Pearce, 2021; Pedersen et al., 2020). A week-long visit was completed in Iqaluit and Resolute Bay before any data collection took place to minimize the following relevant concerns listed in *Negotiating Research Relationships with Inuit Communities: A Guide for Researchers* (Inuit Tapiriit Kanatami and Nunavut Research Institute, 2006):

- Lack of input/consultation with research needs/questions and study design
- Lack of local involvement
- Token inclusion of local expertise
- Lack of recognition/compensation
- Generalization of local knowledge
- Inappropriate research methodology
- Lack of locally beneficial research
- Inadequate reporting and lack of data ownership

Field data was collected at each location twice, during different seasonal conditions. During the field collection campaign, obtaining additional local knowledge regarding the hydraulic and ecological conditions of the rivers was required to understand the impact of the research findings on the community. Other important information to gather was the most optimal method of disseminating the research findings to the community, observations and experiences that provided valuable insight for interpretation of study findings, and local knowledge of environmental and socio-economic realities. In

addition to information gathering, involving community members was crucial for instrumentation set up, operation, and take down.

The site-specific HKE assessment project plan performed for the Spanish River in Sagamok First Nation underwent review and approval from the Sagamok Scientific Committee and the Research Ethics Board of the University of Ottawa. Ultimately, the site was found to not be feasible to HKE extraction, and these findings, along with the data collected during the survey and the derived data was shared with the community. A copy of the summary pamphlet developed to share analysis results with the community is presented in Appendix B. The Spanish River data was also used to validate national estimates of river HKE energy

The site-specific HKE assessment project in Iqaluit, Nunavut on the Iqaluit Kuunga (Sylvia Grinnell) River was performed in collaboration with the 100% Inuit led Qikiqtaaluk Corporation and local renewable energy development company Nunavut Nukkiqsautiit Corporation (NNC), and the data collection was performed with Polar Outfitting, an Inuit-owned and operated outfitting company in Iqaluit. This work required an approved research license from the Nunavut Research Institute, approval from the Research Ethics Board of the University of Ottawa, engagement with the Iqaluit community, and approval from the local Hunters and Trappers Association (Amaruq HTA). Feedback on the project was obtained from the Amaruq HTA, NNC, participants of the SevenGen Indigenous Youth Summit in Iqaluit, and students and professors at the Nunavut Arctic College in Iqaluit. The site on the Iqaluit Kuunga River was found to be feasible, and these findings were shared with the community through the Amaruq HTA, NNC, the SevenGen Summit, and Nunavut Arctic College. A copy of the summary pamphlets developed to share the analysis results with the community is presented in Appendix B. The collected raw data and derived data were transferred to both the Amaruq HTA and NNC for community data ownership.

1.5 Contributions and Novelty of the Study

There are multiple aspects of novelty to this work. This is the first national satellite data-based assessment of river HKE resources, and in performing this national assessment, the first high-resolution dataset of river widths was developed that provides measurements across multiple seasonal flow conditions. Additionally, this work represents the first systematic comparison of surface water mapping methods across multiple geographically diverse regions, each at two different dates. Within this work, the first analysis of turbine deployment location optimization considering different river flow conditions was performed. This is also the first study to evaluate HKE at a fluvial site in the Canadian Arctic. The average annual temperature at the chosen site on the Iqaluit Kuunga River is colder than 97.5% of communities in the Global Arctic, and its

demonstrated feasibility, despite river ice, paves the way for wider exploration of HKE in similarly challenging settings.

This work also represents the first global HKE study of its kind, incorporating newly available datasets that allowed for meter-scale spatial resolution of HKE estimates, making the resulting dataset suitable for community-level decision-making. Unlike prior studies, this work includes direct validation of energy estimates with measurements of river HKE. Additionally, this is the first global-scale HKE assessment that meets International Electrotechnical Commission standards for river HKE estimation, ensuring reproducibility and confidence in the methods applied. Lastly, this is the first socioeconomic evaluation of HKE feasibility in the Arctic, combining community interviews with published literature to identify major barriers to energy transition and also to highlight enabling conditions, resulting in actionable recommendations for policymakers and communities.

1.6 Publications and Presentations

1.6.1 Journal Articles

- 1) **Kirby, K.**, Ferguson, S., Rennie, C.D., Nistor, I., Cousineau, J., 2022. Assessments of available riverine hydrokinetic energy: a review. *Can. J. Civ. Eng.* 49, 839–854. <https://doi.org/10.1139/cjce-2021-0178>.
 - The first author (Katelyn Kirby) was responsible for data curation, formal analysis, investigation, and writing (original draft, review, and editing). A modified preprint of the manuscript is included in Chapter 2 of this thesis.
- 2) **Kirby, K.**, Rennie, C.D., Cousineau, J., Ferguson, S., Nistor, I., 2023. Impacts of seasonal flow variation on riverine hydrokinetic energy resources and optimal turbine location – Case study on the Rivière Rouge, Québec, Canada. *Renew. Energy* 210, 364–374. <https://doi.org/10.1016/j.renene.2023.04.067>
 - The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, validation, visualization, and writing (original draft, review, and editing). A modified preprint of the manuscript is included in Chapter 3 of this thesis.
- 3) **Kirby, K.**, Rennie, C.D., Poot, R., Ferguson, S., Cousineau, J., Nistor, I., 2024. Accuracy of Surface Water Maps Derived from Radar Satellite Imagery Compared to Multispectral Satellite Imagery. *Can. J. Remote Sens.* 50, 2433591. <https://doi.org/10.1080/07038992.2024.2433591>
 - The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing

(original draft, review and editing). A modified preprint of the manuscript is included in Chapter 4 of this thesis.

- 4) **Kirby, K.**, Ferguson, S., Rennie, C.D., Cousineau, J., Nistor, I., 2024. Identification of the best method for detecting surface water in Sentinel-2 multispectral satellite imagery. *Remote Sens. Appl. Soc. Environ.* 101367. <https://doi.org/10.1016/j.rsase.2024>.
 - The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing (original draft, review and editing). A modified preprint of the manuscript is included in Chapter 5 of this thesis.
- 5) **Kirby, K.**, Ferguson, S., Rennie, C.D., Cousineau, J., Burcher, R., Nistor, I., 2026. High-resolution mapping of river hydrokinetic energy resources in Canada using remote sensing. *Renew. Energy* 256, 123970. <https://doi.org/10.1016/j.renene.2025.123970>
 - The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing (original draft, review and editing). A modified preprint of the manuscript is included in Chapter 6 of this thesis.
- 6) **Kirby, K.**, Rennie, C.D., Nistor, I., Johnstone, C., Ordonez Sanchez, S., Fu, S., Cousineau, J., Ferguson, S., Shilton, H., 2026. The in-stream renewable energy potential of rivers for remote communities in the global Arctic. Manuscript submitted for publication (under review in *Nature Communications*).
 - The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing (original draft, review and editing). A modified preprint of the manuscript is included in Chapter 7 of this thesis.

1.6.2 Conference, Symposium and Workshop Proceedings

- 1) **Kirby, K.**, Rennie, C., Ferguson, S., Cousineau, J., Nistor, I., 2025. A High-Resolution National Database of River Widths from Remote Sensing and Cloud-Based Image Processing, in: *Proceedings of the 40th IAHR World Congress - "Innovative Water Engineering for Sustainable Development."* Singapore, p. 1997. https://doi.org/10.64697/978-90-835589-7-4_41WC-P2082-cd
 - The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, software, validation, visualization, writing (original draft, review, and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.

- Awarded John F. Kennedy Student Paper Competition Award by the International Association for Hydro-Environment Engineering and Research. Awarded third place in competition of 120 participants.
- 2) **Kirby, K.**, Rennie, C.D., Ferguson, S., Cousineau, J., Nistor, I., 2025. A high-resolution national database of river widths from remote sensing and cloud-based image processing. Oral presentation at *Graduate Research on Water Technology and Hydraulics (GROWTH) Symposium 2025*, Ottawa.
 - The first author (Katelyn Kirby) was responsible for delivery of the oral presentation at the symposium.
 - 3) **Kirby, K.**, Rennie, C.D., Cousineau, J., Nistor, I., Ferguson, S., 2025. Modelling the River Hydrokinetic Energy at a Bedrock Depth Constriction, in: *Proceedings of the 12th Conference on Fluvial Hydraulics*. Presented at the 12th International Conference on Fluvial Hydraulics, Taylor & Francis, Liverpool, UK, pp. 439–447. <https://doi.org/10.1201/9781003475378-65>
 - The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, validation, visualization, writing (original draft, review, and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.
 - 4) **Kirby, K.**, Fu, S., Ordonez-Sanchez, S., Lavery, G., Bolivar Carbonell, M., Okalik-Musgrove, J., Johnstone, C., Rennie, C., 2024. Harnessing Hydrokinetic Energy for Enhanced Energy Resilience in the Arctic Communities of Canada. Presented at the PAMEC Energy Association, Barranquilla, Colombia.
 - The first author (Katelyn Kirby) was responsible for methodology, data curation, formal analysis, validation, writing (original draft, review, and editing). This extended abstract is not included in this thesis.
 - 5) **Kirby, K.**, Rennie, C.D., Cousineau, J., Ferguson, S., Nistor, I., 2023. Practical Considerations of Conducting River Hydrokinetic Energy Resource Assessments. Presented at the 40th IAHR World Congress - “Rivers Connecting Mountains and Coasts,” Vienna, Austria, pp. 1652–1661. https://doi.org/10.3850/978-90-833476-1-5_iahr40wc-p0049-cd
 - The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, validation, formal analysis, visualization, writing (original draft, review and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.

- 6) **Kirby, K.**, Rennie, C.D., Nistor, I., Cousineau, J., Ferguson, S., 2022. Investigation into the Influence of Flow Variation on Estimated Available Riverine Hydrokinetic Energy by Modelling a Reach of the Rouge River, Quebec, Canada, in: Proceedings of the 39th IAHR World Congress. Presented at the Proceedings of the 39th IAHR World Congress From Snow to Sea, International Association for Hydro-Environment Engineering and Research (IAHR), pp. 2543–2550. <https://doi.org/10.3850/IAHR-39WC2521711920221251>
- The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, validation, formal analysis, visualization, writing (original draft, review and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.
- 7) **Kirby, K.**, Rennie, C., Cousineau, J., Ferguson, S., Nistor, I., 2022. Riverine Hydrokinetic Energy Extraction: Investigation into a Location's Suitability for Turbine Deployment, in: Walbridge, S., Nik-Bakht, M., Ng, K.T.W., Shome, M., Alam, M.S., El Damatty, A., Lovegrove, G. (Eds.), Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021. Springer Nature, Singapore, pp. 677–688. https://doi.org/10.1007/978-981-19-1065-4_56
- The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, validation, formal analysis, visualization, writing (original draft, review and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.
 - Awarded second place for best student paper in the hydrotechnical specialty.

1.7 Additional Research Contributions

The following is a list of publications the author (Katelyn Kirby) led or contributed to, which have been informed by or supported the research described in this thesis:

1.7.1 Conference, Symposium and Workshop Proceedings

- 1) Ghazizadeh, M., **Kirby, K.**, Rey, A., Pilechi, A., Burcher, R., 2026. Advancements in Numerical Simulation of Microplastics Transport in Open Waters: Model Enhancements and Sensitivity Analyses of Boundary Conditions and Settling Velocities. Manuscript submitted for publication (under review in Science of the Total Environment).

- The second author (Katelyn Kirby) was responsible for data curation, formal analysis, visualization, and writing (review and editing). This manuscript is not included in this thesis.
- 2) **Kirby, K.**, Ghazizadeh, M., Pilechi, A., Cousineau, J., 2025a. Exploring the Sensitivity of Microplastic Accumulation Zones in Rivers Using High-Performance Particle Transport Modelling, in: Proceedings of the 40th IAHR World Congress - “Innovative Water Engineering for Sustainable Development.” Singapore, p. 1704. https://doi.org/10.64697/978-90-835589-7-4_41WC-P2080-cd
- The first author (Katelyn Kirby) was responsible for conceptualization, methodology, data curation, formal analysis, investigation, validation, formal analysis, visualization, writing (original draft, review and editing), and delivery of the oral presentation at the conference. This conference paper is not included in this thesis.

1.7.2 Technical Reports

- 1) **Kirby, K.**, Ferguson, S., Rennie, C.D., Nistor, I., Cousineau, J., 2025. Improvement of Canada’s hydrokinetic energy resource database - NRC Publications Archive (Technical Report No. NRC-OCRE-2024-TR-009). National Research Council Canada, Ottawa, ON. <https://doi.org/10.4224/40003535>
- The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing (original draft, review and editing). This report is not included in this thesis.
- 2) **Kirby, K.**, 2022. Hydrokinetic Power Assessment Field Work Report (Technical Report). Ocean, Coastal and River Engineering Research Centre, National Research Council Canada.
- The first author (Katelyn Kirby) was responsible for data curation, formal analysis, investigation, visualization, and writing (review, and editing). This report is not included in this thesis.
- 3) **Kirby, K.**, Ferguson, S., Rennie, C., Nistor, I., Cousineau, J., 2020. Investigation of Methods to Improve Canada’s Hydrokinetic Energy Resource Database (Technical Report No. NRC-OCRE-2020-TR-026). National Research Council Canada.
- The first author (Katelyn Kirby) was responsible for conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing (original draft, review and editing). This report is not included in this thesis.

1.8 Outline of the Thesis

This thesis is organized as shown in Figure 1-1 and is described as follows:

- Chapter 2 (Literature Review) contains a critical review of literature on site-scale and large-scale HKE resource estimation and identified approaches based on new techniques and datasets to improve HKE assessments. This chapter is based on an article published in *Canadian Journal of Civil Engineering*.
- Chapter 3 (Local Hydrokinetic Energy Resource Assessment Case Study) presents the estimation of HKE at a localized river site using the International Electrotechnical Commission's standards for river HKE assessment as well as consideration of the optimal turbine location among changing seasonal flow conditions. This chapter is based on an article published in *Renewable Energy*.
- Chapter 4 (Optimization of Surface Water Mapping Data) describes a comparison of satellite data products, particularly synthetic aperture radar and multispectral, for Earth surface water detection. This chapter is based on an article published in *Canadian Journal of Remote Sensing*.
- Chapter 5 (Optimization of Surface Water Mapping Methods) describes a comparison of satellite data processing methods for detection of Earth surface water as well as the effects of pre- and post-processing steps on the accuracy of the surface water maps. This chapter is based on an article published in *Remote Sensing Applications: Society and Environment*.
- Chapter 6 (River Hydrokinetic Resources in Canada) presents the development and validation of a national database of river HKE estimates. This chapter is based on an article published in *Renewable Energy*.
- Chapter 7 (The Renewable In-Stream Energy Potential of Arctic Rivers for Remote Communities) presents a holistic view of HKE feasibility in the Global Arctic, including a localized feasibility assessment of an Arctic river, analysis of Canadian communities suitable for hydrokinetic energy extraction, development and validation of a Global Arctic river HKE database, and review of socioeconomic realities for Arctic community renewable energy transitions. This chapter is based on a draft manuscript that is presently submitted to *Nature Communications*.
- Chapter 8 (Findings, Interpretation, and Future Work) synthesizes the findings of the literature review, satellite imagery data and methods comparisons, national and global HKE resource assessments, and technical and practical resource analyses.
- Chapter 9 (Conclusion).
- Supplementary information is provided in the Appendices.

Chapter 2. Literature Review

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Ferguson, S., Rennie, C.D., Nistor, I., Cousineau, J., 2022. Assessments of available riverine hydrokinetic energy: a review. *Can. J. Civ. Eng.* 49, 839–854. <https://doi.org/10.1139/cjce-2021-0178>.

Abstract:

Methods of estimating riverine hydrokinetic energy (HKE) for localized and regional studies are reviewed, evaluated, and compared. It was found that localized HKE studies were not entirely consistent, with the most common discrepancies being discharge variability characterization, uncertainty analysis, and the amount of data used to derive the results. The issues associated with localized assessments were amplified for regional assessments. Regional HKE assessments were less common, the methods were less consistent across studies, and the amount and type of data available varied widely across regions. New techniques and technologies, developed in Canada and globally, were evaluated for their usefulness to improve regional HKE assessments. Emphasis was put on satellite remote sensing methods to estimate discharge and channel dimensions, as well as regionalized curve fitting to estimate channel roughness. The review of new techniques suggests that accuracy of the results is dependent on the amount and quality of the data available.

Keywords: Satellite remote sensing; resource assessment; river hydraulics; hydrology regionalization; bathymetry estimation

2.1 Introduction

The extraction of hydrokinetic energy (HKE) involves utilizing tidal or wave energy of the ocean or velocity energy of a river to turn a turbine to generate electricity. HKE technology is referred to as “run-of-river”, because it does not greatly impact the discharge of the river, as compared to conventional hydroelectric dams, which alter a river’s natural discharge and bathymetry. However, the caveat of HKE power is that it is reliant on the conditions of the river environment that it is introduced into. This includes seasonal discharge variation, depth and width limitations, accessibility issues, and even blockages due to vegetation, large woody debris, or ice. Additionally, HKE is not as efficient as conventional hydropower with an efficiency limit of 59.3%, defined as the Betz limit (Yuce and Muratoglu, 2015). HKE may provide a promising alternative to conventional electricity generation in Canada and globally, and thus it has been gaining attention over the past two decades. Particularly in Canada, emphasis has been put upon

exploring power generation methods that do not create greenhouse gases (GHGs), which are the leading cause of global climate change. Canada entered the Paris agreement in an attempt to keep the earth's temperature rise under 2°C due to global climate change (Environment and Climate Change Canada, 2022). To do this, Canada pledged to transition to 90% non-GHG-emitting electricity by 2030 (Environment and Climate Change Canada, 2017). Another initiative that Canada has created is the Off-Diesel Challenge from the Clean Energy for Rural and Remote Communities program by Natural Resources Canada, which aims to reduce reliance on diesel fuel for rural and remote communities (Natural Resources Canada, 2017). Other notable initiatives are the Low Carbon Economy Fund (Environment and Climate Change Canada, 2017), the Clean Growth Hub (Innovation Government of Canada, 2021), and the Powering Past Coal Alliance (Natural Resources Canada, 2017). Other countries around the globe have such initiatives as well. To bolster this increased interest in non-GHG-emitting electricity sources, HKE potential should be thoroughly explored to understand if it is a feasible alternative, and, if so, where would it be most suitable. This review only covers riverine HKE potential.

To understand if HKE is feasible, local and regional studies have been conducted in various areas across the globe to quantify the amount of HKE potential in rivers. Regional types of studies are usually completed on the national or provincial/state scale. Their intents are to locate areas of high HKE potential to further investigate on a smaller or local scale, to quantify the total possible amount of HKE to decide if investment is wise, and to make the information readily available for potential investors. Some common factors that may be barriers to a feasible HKE installation in an area are depth limitations (usually not feasible for less than 2 m) preventing the physical installation of a turbine unit or array, low velocity (approximately less than 1.5 m/s) indicating that there is low power extraction potential and poor return on investment, and other technical, societal, environmental, and economic considerations that will not be discussed in this paper. The cost of in-depth, site-specific hydrologic studies can be restrictive, as most local hydro developments cannot afford these types of studies; therefore, regional HKE assessments are employed to evaluate if a location may be profitable before significant investment is made (Judge et al., 1988). The objectives of this review are to understand where HKE resource assessment research is at and how it has evolved, to evaluate possible areas of improvement or advancements in HKE estimation (i.e., new technology or tools available), and to draw conclusions about research gaps and methodological requirements in HKE assessments. To this end, this study will evaluate both local (i.e., single location or single reach) and regional (i.e., regional, provincial, or national) HKE assessments in Canada and globally to understand the methods that currently exist, to explore new technologies or advancements that may improve the assessments previously evaluated, and finally to make recommendations on further research based on its findings.

2.2 Local Hydrokinetic Energy Resource Assessments

To begin, the methods of local HKE potential assessments will be evaluated, because these types of assessments are more numerous, and they have been conducted more recently compared to regional assessments. Therefore, they will provide more insight into the current state of HKE assessments. Also, they will provide an idea of the limitations that arise when attempting to duplicate local HKE assessment methods on a regional scale. Local HKE assessments refer to either single deployment location, single reach with multiple deployment locations, or multiple (two or three) reach assessments. In general, because the size of the study area is small for local assessments, more effort is placed into ensuring high quality data are available to begin the assessment (e.g., spatially intense field data, light detection and ranging (LiDAR) or other high-resolution imagery, etc.), and this contributes to more accurate results. One of the aims in assessing these local studies, separately from regional studies, is to understand if and how the methods can be applied to regional assessments and to define the limitations of assessments at the local scale. More local assessments exist, and it is more state-of-the-art than regional assessments (i.e., the most recent local studies are 2011 to 2020 compared to 1984 to 2020 for regional). As such, it was useful to evaluate local studies first separately to understand the methods used and if those methods were scalable. In tandem with this objective, the state-of-the-art in local HKE resource assessments will be explored and any caveats to the methods will be discussed.

Table 2-1: Local hydrokinetic energy resource assessments. Acronyms are defined in the text.

Study #	Authors	Assessment approach	Flow variation consideration	Estimation method(s)	Error analysis method(s)	Quantified error result(s)
Standard	IEC (2019)	Hydrokinetic	15-point FDC and VDC	VDC and AEP estimation via 15-point FDC based on 10 years of available or synthetic, modelled discharge data	Model calibration using agreement between depth-averaged velocity and validation using agreement between depth-averaged velocity and vertical velocity variation	5% or less for calibration and 10% or less for depth-averaged velocity validation and 25% or less for vertical velocity validation
1)	Arango (2011)	Hydrokinetic	5 percentile, 50 percentile, and 95 percentile	Cumulative probability distribution functions of discharge and physical and computational fluid dynamic models	None	None
2)	Duvoy and Toniolo (2012)	Hydrokinetic	Not considered	Hydrodynamic model using data collected in field campaign	None	None
3)	Petrie et al. (2014)	Hydrokinetic	Not considered	Velocity data collected in field campaign	Data expected to contain error over threshold limit was discarded	None
4)	Kalnacs et al. (2014)	Hydrokinetic	Not considered	Velocity data collected in field campaign	Visual comparison between collected data and available statistical data	None
5)	Punys et al. (2015)	Hydrokinetic	Mean annual, bankfull, and low discharge	HEC-RAS hydraulic model to estimate discharge, channel geometry, and velocity using historical data	Visual comparison between hydraulic model parameters and hydrologic model parameters	None
6)	Cornett and Faure (2015)	Hydrokinetic	Variation over a typical year	Hydrograph estimation and TELEMAC-2D hydrodynamic model using historical data	Validation using historical discharge and water level for several gauging stations	No information available
7)	Filizola et al. (2015)	Hydrokinetic	Not considered	Velocity flow field data used to calculate theoretical hydrokinetic power	None	None
8)	Montoya Ramirez, et al. (2016)	Hydrokinetic	Joint probability curves and duration curves using 100 h of data	HEC-RAS hydraulic model with hourly discharge data to simulate mean velocity	None	None
9)	Nordino (2016)	Hydrokinetic	VDC from five years of historical data	VDC generation from historical data	None	None
10)	Nhabetse et al. (2017)	Hydrokinetic	VDC from five years of historical data	VDC generation from historical data	None	None
11)	Holanda et al. (2017)	Hydrokinetic	Maximum, minimum, and mean discharge	Hydrodynamic model to simulate velocity	Validation against field measurements using average error	Average error of 8.77% and maximum error of 22.00% in simulated velocity
12)	Saupi et al. (2018)	Hydrokinetic	120 days of data used to develop regression	Best fit regression equations	Validation against field measurements using R^2	R^2 of 87.4% and 87.9% for water level and velocity, respectively
13)	Lata-Garcia et al. (2018)	Hydrokinetic	Not considered	HEC-RAS hydraulic model to simulate velocity profile	None	None
14)	Kasman et al. (2019)	Hydrokinetic	Five years of data used to develop simulation	Computational fluid dynamics simulation	Validated against field measurements using average error	Average error of 2.9% and 0.6% for either cross section validated
15)	Silva dos Santos et al. (2019)	Hydrokinetic	Relationships based on 3 to 25 years of data, depending on the location	Hydraulic geometry approach and numerical model to simulate velocity profiles	Comparison between field measurements using average error	Average error of 11.0% and 13.25% for either location
16)	Adeogun et al. (2020)	Hydropower	Not considered	SWAT model and GIS techniques to simulate flow and hydrological parameters to estimate discharge and hydraulic head, respectively	Nash–Sutcliffe Efficiency and R^2	0.70 for NSE and 0.74 for R^2
17)	Ali et al. (2020)	Hydropower	Not considered	SWAT model and GIS techniques to simulate flow and hydrological parameters to estimate discharge and hydraulic head, respectively	Nash–Sutcliffe Efficiency and R^2	0.65 for NSE and 0.68 for R^2

The International Electrotechnical Commission (IEC) published standards for local HKE assessments under technical specification 62600-301 Marine Energy – Wave, Tidal and Other Water Current Converters, Part 301: River Energy Resource Assessment in 2019 (IEC, 2019). This document will be evaluated first in this review paper because it is the most comprehensive, and all other studies will be compared to its methodologies. Essentially, the specification provides required steps and suggested methods to process available gauged data and/or field data into an estimate of riverine HKE potential. It

provides other requirements on top of the methodological requirements, such as documentation, model calibration, result validation, and acceptable model error. Overall, the goal is to generate a velocity duration curve (VDC), from which the potential HKE, or annual energy production (AEP), can be calculated. The first step is to generate a 15-point flow duration curve (FDC), as this will account for the empirical variation of the river discharge. The FDC can be generated from ten years of discharge data for the location if available. If ten years of data are not available, a hydrological model should be employed to generate ten years of synthetic discharge data. That generated data should be validated with one year of available discharge data for the location. Therefore, as per the IEC standards, at least one year of discharge data is required for any potential HKE development location. The next step is to create a curve fit for the velocity-discharge measurement, and this step also depends on the amount of data readily available for the location. VDCs can be developed directly at locations with 5 velocity-discharge measurements at the specific renewable energy convertor (REC) location (i.e., at the particular location within the cross section of the channel) for “small” projects. The IEC defines a small project as projects which have a project blockage ratio (ratio of moving and non-moving area of all RECs to average channel cross-sectional area) of less than 5%, projects in which each REC has at least ten equivalent diameters spacing from each other. This also includes projects that have not introduced any flow modification to increase the available power. If there are not five velocity-discharge measurements available for the REC location or if the project is “large” (any projects which do not meet the small project requirements), a model shall be used to estimate this relationship. To be able to use a model, three different stage-discharge conditions are needed for the model input, two channel transects of velocity for three different discharge conditions are needed for the model calibration, and velocity-discharge measurements at two REC locations for three different discharge conditions are needed for verification. The IEC standards reference the International Hydrographic Organization’s Standards for Hydrographic Surveys for information on how to properly collect field data (International Hydrographic Organization, 2020). The standards also indicate that the effects of the turbine being introduced into the river need to be considered and estimated for projects deemed to be large. When the velocity data are available, either from modelling or measurements, a curve should be fit to the velocity-discharge relationship for each REC location within the river. From that, the VDC can be generated, and the AEP can be calculated for each REC. The document describes types of models that can be used for the assessments and their calibration and validation requirements, as well as the benefits or drawbacks of each type of model. Overall, the standards leave the choice of model to be used up to the team conducting the study, as long as the model meets the accuracy requirements of the HKE assessment. The assessment can either be based on an REC with known parameters (i.e., provided by a manufacturer) or from a generic REC with generic parameters. When comparing the output of the model to measurements, the

relative mean squared difference between the two should not be greater than 10% (IEC, 2019).

Neary et al. (2011) developed a best practice manual for the collection of field measurement data required for the assessment of potential HKE at identified deployment sites. The document was published by the Oak Ridge National Laboratory. The purpose of the guideline was to increase accuracy of HKE assessments with the goal of comparison to conventional electricity generation and other renewables. When the document was published in 2011, assessments of the time had power densities averaged over grid cells of 300-meter to 500-meter resolution. Neary et al. (2011) argued that models needed to be more refined, such as those created with spatially intense field data using acoustic Doppler current profiler (ADCP), acoustic Doppler velocimeter (ADV), or other such measuring device, for development to take place. The complexities of estimating HKE in a stream were recognized by Neary et al. (2011), as it was mentioned that the following variables could change conditions along the length of the river reach: bed sediment, grain, and form roughness; secondary circulation caused by channel form; wind shear on the water surface; and the presence of structures that could create surface wakes, vortex shedding, and increased turbulence in the wake. Therefore, various measurements are required to properly characterize the complexities of velocity in the reach, which include reach bathymetry, bed substrates, in-stream flow structures, properties of the fluid, and flow field. For reach bathymetry, Neary et al. (2011) recommends the use of single and multi-beam depth echosounders (SBE, MBE) coupled with GPS. Particularly, it is important to capture the bed form at the location of interest, such as the wavelength and height of dunes, ripples, or antidunes. For bed substrate, samples should be taken at the location of interest to characterize the particle size, specific gravity, shape factor, and fall size of the bed and bank materials. In order to properly model the effect of in-stream structures on the AEP available and the effects of introducing a turbine into the river environment, measurements of the structures present should be available. Properties of the fluid that should be measured are temperature, density, kinematic viscosity, and salinity. The turbidity of the fluid can cause changes to the flow field, so it should be measured as well. Finally, one should attempt to understand the turbulence and how it effects the flow field velocity. In general, the flow field velocity is time averaged because of temporal variability induced by turbulence effects (Neary and Gunawan, 2011).

Local studies are reviewed to evaluate their methodology and their conformance to the previously reviewed standards and guidelines of HKE assessments. Also, reviewing local studies will provide insight to the limitations of regional studies and may suggest possible techniques of overcoming these limitations. Arango (2011) conducted a study of 4 potential identified HKE extraction sites on the Columbia River downstream of Wanapum and Priest Rapids Dams, both at channel constrictions. 15 years of discharge

information were provided in the Columbia River Data Access data bank and from Grant PUD operational records. Cumulative probability functions were generated from the available discharge data. Bathymetry data at each dam tailrace were available via field measurements from the Iowa Institute of Hydraulic Research (IIHR). The vertical velocity profile and bathymetry data used in the study were simulated by physical and computation fluid dynamic models of the two dam tailraces. The modelled data were developed and provided by the IIHR. Time-averaged, three-dimensional velocity profiles were generated for low, mean, and high discharge conditions (5% percentile, 50% percentile, and 95% percentile, respectively) at each channel transect. HKE density was calculated through the water column at each site using the simulated velocity profiles, discharge probability distribution, and the parameters of the turbines under consideration. Arango (2011) mentioned that there is not sufficient information provided by the IIHR to validate the data provided by the IIHR models. As such, the error in the data utilized in the study and final results were not quantified (Arango, 2011).

Duvoy and Toniolo (2012) studied the HKE potential at a location on the Tanana River at Nenana, Alaska. Discharge data were obtained from a United States Geological Survey (USGS) gauging station in the area and bathymetric surveys were conducted on August 8, 9, 12, and 13, 2010. During the bathymetric survey campaign, acoustic doppler current profiler (ADCP) measurements were taken for velocity profiles and slope data were collected. This study employed HYDROKAL, an external module for the CCHE2D hydrodynamic model which utilizes velocity estimates from CCHE2D to calculate instantaneous power density in the channel. Seasonal variation of the discharge was not considered in this study, as the stream power was only simulated for the duration of the field data collection. Although Duvoy and Toniolo (2012) stated that the purpose of the study was to test the capabilities of the HYDROKAL model rather than to conduct a full HKE assessment study to estimate the AEP, it is useful to review the inputs that were needed for the hydrokinetic energy assessment model and the caveats of the research. For validation of the model's velocity estimates, the model output was compared to ADCP measurements visually. The visual comparison showed good correlation between the model output and the measured velocity. Because the model output is averaged in the vertical direction and the ADCP provides vertical velocity profiles along the transect, Duvoy and Toniolo (2012) argued that strict validation of the results was not possible.

Petrie et al. (2014) utilized ADCP measurements to identify locations within a reach with fast-moving water and thus high HKE potential. The ADCP data used in the study were collected on two cross sections of the lower Roanoke River, USA and was processed to extract channel depth, depth-averaged velocity, flow direction, and mean 3-dimensional velocity profiles. The data was collected at each location within the reach for a minimum of 1200s at a single discharge condition. As such, the influence of the discharge condition on the velocity flow field and the associated locations with high HKE

potential was not considered in this study. The error associated with the ADCP measurements was not addressed in this study; however, the authors comment on directional errors that were observed in the measurements close to the riverbank. As such, measurements that were expected to contain error over a specified threshold were automatically removed from the record to reduce overall inaccuracy in the results (Petrie et al., 2014).

A study conducted by Kalnacs et al. (2014) used direct in-river velocity measurements to investigate optimal locations for turbine deployment within Daugava River, Latvia. The researchers referred to Chapter 6 of the Manual on Stream Gauging (World Meteorological Organization, 2010) for field measurement procedures, but it is not clear what equipment the velocity measurements were taken with. The validation of the velocity field data was completed by visually comparing the available statistical data from the Latvia State-financed observation station network against the measured data's calculated flow rate. Kalnacs et al. (2014) state that the results of the comparison imply that the measured data comply and could be used to calculate estimates of HKE in the reach.

Punys et al. (2015) conducted a study of the Neris River in Lithuania where between 9 to 52 years of gauging station discharge data were available, depending on the study area. Stage, velocity, and cross-sectional area data were also available at these gauged locations. From these data, discharge-stage, discharge-velocity, and discharge-area relationships were developed as the hydrological models for the study area. The HEC-RAS hydraulic model was used to simulate mean annual, bankfull, and low discharges from which velocity, bathymetry, and stream power were also estimated. The model was calibrated using field measurements at 27 sites along the river, from the mouth to the border of Lithuania. Validation of the model was completed with stage, velocity, discharge, and cross-sectional area data from three gauging stations. The resulting simulated velocity was used to calculate HKE density in three discharge conditions. The parameters generated by the hydraulic model were compared to those provided by the hydrologic model and good correlation in the stage datasets were observed. However, scattering was present when visually comparing the velocities and cross-sectional area plots.

Cornett and Faure (2015) conducted a study on the St. Lawrence River at two locations: the first one between Cornwall and Montreal (80km long reach) and the second one downstream of Montreal from Sorel into the Gulf of St. Lawrence (800km long reach). The second location presented a challenge, as flow is both tidal and fluvial. Historical discharge information was used to develop a hydrograph, and bathymetry data were obtained from the Meteorological Services Branch of Environment Canada as well as additional survey data from the Seaway International Bridge Corporation and Verdant Power Canada. TELEMAC-2D was the model used to simulate variation in discharge and

water level over a typical year by solving the vertically averaged shallow water equations (i.e., Saint-Venant) in two dimensions. The available HKE was calculated from the simulated velocity values. The model was validated using historical discharge values and water levels (Cornett and Faure, 2015).

Filizola et al. (2015) estimated the HKE potential at eight locations in the Brazilian Amazon River Basin. Originally, 54 sites were considered in the analysis; however, with data availability and desirable hydrological characteristic constraints applied, only eight were suitable for further analysis. Data availability included velocity flow fields which were measured with ADCP apart from this study. The velocity flow fields were used to determine the optimum location within the reach for HKE extraction as well as calculation of the extractable HKE. The available extractable area for each river cross section was assumed to be 1000m³. No error analysis was conducted on the ADCP data used in the evaluation (Filizola et al., 2015).

Montoya Ramírez et al. (2016) studied the feasibility of deploying HKE turbines in the tailrace of dams at two hydropower plant locations in Columbia. To obtain time series of mean flow velocity, stream velocity, and water depth, the non-stationary one-dimensional HEC-RAS hydraulic model Version 4.1 was used with hourly flow discharge input data provided by the hydropower plants. The measured geometries of the tailraces were also available from the hydropower plants. Montoya Ramírez et al. (2016) then compared hydraulic performance data from HKE turbine manufacturers with the flow velocity and water depth present in the tailrace to determine if the installation was feasible. Because the study was intended to satisfy a preliminary evaluation of feasibility, no validation or error analysis of the generated data was conducted (Montoya Ramírez et al., 2016).

Nordino (2016) and Nhabetse et al. (2017) employed similar methods to generate VDCs for the Maputo River, Mozambique and Umbeluzi River, Mozambique, respectively, from which potential HKE could be calculated. To generate the VDCs, five years of historical velocity data was used, and the flow velocities of the rivers were compared to the required design velocities of five HKE turbines. This, and consideration of the required channel depths for the turbines, constituted the feasibility analysis of the study, and potential HKE was calculated for both rivers from the VDC.

Holanda et al. (2017) studied the HKE potential in the Tocantins River in Brazil. Discharge data were available for the location from 2007 to 2014 and bathymetry data were provided by the Eletronorte/Elektrobras Company who collected it in September 2004. Three discharge conditions were considered in the analysis: maximum, minimum, and mean. For simulation of the velocity, a 2D longitudinal-transverse hydrodynamic model and the Saint-Venant equation were used. Power was calculated using the kinetic instantaneous power equation. Validation of the model results was completed using

ADCP field measurements conducted in 2012 and 2013. The comparison resulted in an average velocity error of 8.77% and a maximum error in the dataset of 22.00% (Holanda et al., 2017).

In a study conducted by Saupi et al. (2018) on the Batang Belleh River in Malaysia, regression equations were generated to estimate both water level and velocity at an ungauged location. To develop the regression equations, the Pearson Correlation Analysis techniques were used to determine the variables' correlation strengths, optimize parameters, and determine best fit. The regression models were validated against water level and water velocity data collected during different time periods than those used to generate the regression models. Among linear, logarithmic, quadratic, cubic, and exponential regression model types, the most suitable model was selected based on the highest R^2 value. The regression was conducted between water level data at a gauge station and 120 days of water level data collected at the remote location as well as between water level and 105 samples of ADCP velocity data. To validate the regression equations, 90 days of water level data were used, and the velocity data used for the validation were measured from March 2015 to May 2015. The validation resulted in R^2 of 87.4% and 87.9% for the water level and water velocity respectively. Saupi et al. (2018) state that these regression equations can be used to generate water velocity time series for remote, type-C, unregulated rivers.

Lata-Garcia et al. (2018) conducted their study on the Guayas River in Ecuador where one discharge of 3500 m³/s was incorporated to find the best possible location for the turbine for maximum HKE extraction. The channel bathymetry was available, and the velocities used for validation in the study were provided by the Ecuadorian Navy over one year where measurements were taken three times per day. The model used to simulate the velocity profile at the area of interest was HEC-RAS. To calculate the potential HKE available, the HOMER simulation tool was used to estimate HKE with velocity and the turbine parameters as inputs. No validation results were presented in the paper (Lata-García et al., 2018).

In a study conducted by Kasman et al. (2019) downstream of the Balambano hydropower plant on the Balambano River in Indonesia, a computational fluid dynamics simulation is used to develop ten years of daily flow fluctuation data and the associated average flow velocity to estimate the available HKE. Inputs to the simulation are the river bathymetry collected via echo sounding equipment and flow data from 2012 to 2017 provided by the hydropower plant. To validate the output of the simulation, point velocity measurements were taken in the river at two cross sections with each cross section divided into 9 measurement points. The type and model of the equipment used to measure the velocity were not specified. The simulation's output was averaged and compared to the averaged measured velocity and resulted in errors of 2.9% and 0.6% for the two cross sections (Kasman et al., 2019).

Silva dos Santos et al. (2019) studied the HKE potential on the Amazon River at two locations downstream of hydropower plants in Northern Brazil. Discharge data were available for 2014 and historical discharge-area (wet area) and discharge-velocity curves were provided by the hydropower plant management. The hydraulic geometry (HG) relationships were based on either 3 years or 25 years of data, depending on the location. Bathymetry studies were conducted and included the use of a multi-frequency echo sounder as well as an ADCP for velocity measurements. The length of the river segment studied was 5 km long with 61 measured cross sections at one location and 64 measured cross sections at the other. A numerical model was used for the simulation of velocity profiles at locations that were expected to have high velocities. Experimental results were compared against the numerical model velocity results. Average deviations were 11.0% and 13.2% for each location. The simulated velocities were used to calculate the HKE potential, and the deviations found in the velocity results were not carried forward into the power calculations. Seasonal variability of discharge was accounted for by presenting monthly potential HKE results rather than a yearly total (Santos et al., 2019).

Adeogun et al. (2020) and Ali et al. (2020) conducted similar studies where GIS techniques and the SWAT model were employed to predict flow and hydrological parameters for estimation of HKE. Adeogun et al. (2020) estimated HKE potential on the Asa, the Awun, and the Oyun Rivers in Nigeria, whereas the Ali et al. (2020) study was conducted on the U-Tapao River in Thailand. HKE was estimated using the hydropower equation with flow and hydraulic head as inputs. Hydraulic head was calculated using the difference between the elevation, provided by digital elevation models (DEMs), at the beginning of the river segment to the end of the river segment. When validated, the SWAT model showed a Nash-Sutcliffe Efficiency (NSE) of 0.70 and an R^2 of 0.74 for Adeogun et al. (2020). The validation for the study conducted by Ali et al. (2020) resulted in an NSE of 0.65 and an R^2 of 0.68.

While the methods reviewed above share several similarities, they also exhibit inconsistencies that the IEC (2019) standards aim to address. Primarily, a great majority of the methods utilize some variation of the kinetic instantaneous power equation shown below:

$$[2-1] P_K = \frac{1}{2} \rho A v^3$$

Where P_K is the potential HKE, ρ is the density of the fluid, A is the area of the river cross section, and v is the velocity. Some other variations include power density and the addition of the power coefficient (a variable that converts the HKE estimate from theoretical to technical), respectively:

$$[2-2] P_K/A = \frac{1}{2} \rho v^3$$

$$[2-3] P_K/A = \frac{1}{2} \rho v^3 C_p$$

where P_K/A is the power density and C_p is the power coefficient (Duvoy and Toniolo, 2012). Overall, none of the studies investigated met the standards of the IEC; however, this is likely due to the time in which they were published. The studies were published from 2011 to 2020 and the IEC standards were published in 2019. The two most common aspects of the studies that did not meet the IEC standards were capturing the variability of flow and calibration and validation of the model used. For proper representation of the variability of discharge, either the discharge data used were not available for ten or more years, or when the proper amount of data were available, FDCs were not developed to characterize the variability of discharge. When the discharge data were not available for ten or more years, few studies attempted to simulate ten years of discharge data using numerical modelling to develop an FDC. However, most of the locations considered in the studies were either directly at a tailrace of a dam or on a river that was regulated. Therefore, inaccuracies caused by not properly considering the seasonal and annual variability of discharge may be less pronounced in these types of regulated watersheds or even in watersheds of a particular hydrology (e.g., glacially fed channels are generally less impacted by annual variability (Ashmore and Church, 2001)). Most of the studies used some type of modelling to simulate velocity within the channel. It was found that there was insufficient calibration and/or validation of most of the models, that the calibration and/or validation of the models were not described in enough detail to assess if the methods were suitable, or that the measure of success in which the models predicted velocity was not consistent across the studies. However, for all of these findings, the IEC standards provide a solution.

2.3 Regional Hydrokinetic Energy Resource Assessments

Dissimilar from local HKE assessments, there are no published standards, specifications, or rules-of-thumb for regional types of HKE assessments. This section will explore and evaluate seven regional HKE assessments from 1980 to 2014 in order to discover similarities between the studies, evaluate the methodologies and accuracies of the assessments, and attempt to draw conclusions about what is needed (e.g., data requirements, techniques, standards, etc.) to improve such assessments.

Table 2-2: Regional hydrokinetic energy resource assessments. Acronyms are defined in the text.

Study #	Authors	Assessment approach	Flow variation consideration	Estimation method(s)	Error analysis method(s)	Quantified error result(s)
1)	UMA Group (1980) for NRC	Hydrokinetic power	No information available	Manning's equation	No information available	No information available
2)	Acres Consulting Services Limited (1984)	Hydropower	Maximum, mean, minimum	Multiple regression technique for development of characteristic relationships of region using turbinable curve	R^2	0.81, 0.66, 0.44 for maximum, mean, and minimum, respectively
3)	Miller et al. (1986)	Hydrokinetic power	No information available	Relationships between (1) discharge and drainage area and (2) drainage area and distance upstream from mouth of river and use of Manning's equation	No information available	No information available
4)	USDOE (2004)	Hydropower	No information available	Drainage area, precipitation, and temperature relationships to estimate discharge using GIS tools	Standard error for discharge and RMSE for hydraulic head	$\pm 9\%$ to $\pm 96\%$ for discharge, ± 3 m for hydraulic head
5)	Kerr Wood Leidal Associates (2008)	Hydropower	Normal year, low-discharge year, and a high demand period	Hydropower assessment model	No information available	No information available
6)	Jacobson (2012) for EPRI	Hydrokinetic power and hydropower	5, 25, 50, 75, and 95 percentiles	HEC-RAS model and application of estimated recovery factor	Percent deviation	77% average deviation for discharge between estimated and gauge station
7)	NRC or the National Academies (National Research Council 2013)	N/A, critique of Jacobson (2012) for EPRI				
8)	Jakimavičius et al. (2014)	Hydropower	Average multiannual	Hydraulic geometry approach	Average relative error of depth, width, and velocity	14.0%, 17.9%, and 19.0% for depth, width, and velocity, respectively
9)	Jenkinson and Bomhof (2014)	Hydrokinetic power and hydropower	17-point FDC	Multiple linear regression coupled with canonical correlation analysis and hydraulic geometry approach	Monte Carlo technique used to determine confidence percentages in the results	97.5% confidence in 433 GW hydropower estimation and 97.5% confidence in 29 GW hydrokinetic power estimate
10)	Cruz et al. (2020)	Hydrokinetic power	Daily average	Numerical model to estimate daily average cross-sectional velocity	Average error	3.07% and 3.13% for flow and velocity, respectively

The first known HKE assessment of this type was completed by the UMA Group (1980) for the National Research Council (NRC) in 1980. The goal of the study was to evaluate the total amount of HKE potentially available in Canadian rivers and streams. The study was limited to the largest rivers in Canada with discharges greater than 450m³/s, velocities greater than 1.5m/s, channel widths greater than 50m, and channel depths greater than 3m. The study was also limited to reaches for which there were 20 or more years of gauged data. Manning's equation was used for discharge velocity estimation in this case. Limited information is available on the actual techniques used in this assessment. Geographic information system (GIS) techniques were limited at the time (UMA Group, 1980).

The next HKE assessment of this type was conducted in 1984 by Acres Consulting Services Limited (1984). The intent of this Canada-wide study was to decide whether additional funds should be invested to further investigate specific sites. This study divided Canada into eleven regions with similar climatological and physiographic characteristics, within which data from between 11 to 23 gauging stations and the characteristics of the areas were used to develop hydrologic relationships. The hydrologic relationships, called turbinable curves, characterized the dependence of the turbinable discharge (the flow that can be passed through a turbine at a particular design discharge) on the design discharge in each of the eleven regions. Physiographic characteristics were determined from 1:250,000 and 1:500,000 scale maps, and the following characteristics were considered in the regional analysis from various government maps: drainage age, basin perimeter, on-channel lake area, off-channel lake area, swamp area, mean annual runoff, mean annual temperature, longitude. A multiple regression technique was used to develop the relationships between characteristics of the regions and the turbinable curve fitting variables. The following equation is the regression model of the turbinable flow curve used for all eleven regions:

$$[2-4] Q_T = \phi_T + \theta Q_D + \alpha(Q_D)^2 + \beta_T(Q_D)^3 + \gamma_T(Q_D)^4 + \kappa_T(Q_D)^5$$

Where Q_D is the design discharge and ϕ , β , γ , and κ are described with the following equations:

$$[2-5] \phi_T = 0$$

$$[2-6] \beta_T = \frac{C^2(Z-6\alpha)-12C\theta+20}{2C^3}$$

$$[2-7] \gamma_T = \frac{C^2(3\alpha-Z_T)+8C\theta-15}{C^4}$$

$$[2-8] \kappa_T = \frac{C^2(Z_T-2\alpha)-6C\theta+12}{2C^5}$$

The best curves from the regression analysis were chosen based on statistical (i.e., R^2 values) and physical significance, and the prior five-degree polynomial equations were fit

to the curves. As shown by Equations 2-4 to 2-8, only Z_T , C , θ , and α were to be determined for each region to develop the turbinable curves. These values depend on the aforementioned physiographic characteristics of the regions. The intent of this study's technique was to be able to estimate potential hydropower, using the following equation, rather than Equation 2-1 or Equation 2-2:

$$[2-9] P_H = \gamma H Q$$

Where P_H is the potential hydropower, γ is the fluid's specific weight, H is the hydraulic head, and Q is the river discharge. The errors in this method arise from the curve fitting method where R^2 ranged from 0.81, 0.66, and 0.44 for the maximum, mean, and minimum and from the physiographic and climatic data used in the assessment (Acres Consulting Services Limited, 1984; Judge et al., 1988).

Miller et al. (1986) conducted a study of potential HKE in the U.S. in 1986 that employed the use of USGS gauged river data for discharge and topographic maps for channel slope and geometry. The study scope was limited to rivers with discharges greater than 113m³/s and velocities greater than 1.3m/s. Discharge was estimated at ungauged reaches by developing relationships between discharge and drainage area and then developing relationships between drainage area and the distance upstream from the mouth of the river. Similar to the UMA Group (1980) study, Manning's equation was used for velocity estimation. Limited information is available on this study, its accuracy, and its outcomes (Miller et al., 1986).

The U.S. Department of Energy (DOE) (2004) conducted an assessment for all available low-head hydropower in the U.S. in 2004. The U.S. DOE (2004) identified 18 unique regions and the following regression equation was used to estimate the mean annual discharge:

$$[2-10] Q_{ma} = e^{a_{ma}} \times A_d^{b_{ma}} \times P_{ma}^{c_{ma}} \times T_{ma}^{d_{ma}}$$

Where Q_{ma} is the mean annual discharge (m³/s), A_d is the drainage area (km²), P_{ma} is the mean annual precipitation (mm/year), T_{ma} is the mean annual temperature multiplied by a factor of ten (°F), and a_{ma} , b_{ma} , c_{ma} , and d_{ma} are specific exponents calibrated to the unique 18 regions. To the authors' knowledge, this was the first type of this assessment that made use of GIS tools and DEMs to estimate hydropower. Hydraulic head was calculated using the elevation difference between the two points on either end of the stream segment in consideration. An equation similar to Equation 2-9 was used to calculate the hydropower of the stream segments, and the utilized hydropower that was extracted at the time (i.e., from hydroelectric dams already in existence) was subtracted from the total calculated hydropower. This yielded the result of available power potential. The study also categorized river segments into the following power and technology classes, based on the available power and hydraulic head: high head/high power, low

head/high power, and high head/low power. As for the approximated error in the final calculated values, standard errors were propagated through the discharge estimates, to the individual stream power estimates, and finally to the total power estimate. Standard errors of the discharge estimates for each region varied from $\pm 9\%$ to $\pm 96\%$, depending on the region (Lower Colorado had the highest error); therefore, the U.S. DOE (2004) stated that the uncertainties in the final power estimates were at least these values. Error was also recognized to result from the elevation data used to estimate hydraulic head. It was calculated that the root mean square error (RMSE) of the hydraulic head of each reach was $\pm 3\text{m}$ (U.S. Department of Energy, 2004).

Kerr Wood Liedel Associates (2008) developed the Rapid Hydropower Assessment Model (RHAM) for a regional assessment of small hydropower in British Columbia (BC), Canada. The RHAM model is GIS based and requires DEMs and hydrology data as input to calculate potential hydropower using an equation similar to Equation 2-9. The DEMs used in the study were provided by Natural Resources Canada (NRCan) and the hydrology data were provided by the BC Ministry of Environment. Seasonal variability of discharge was accounted for by considering a “normal” year, a “low-discharge” year, and a “high demand period” to indicate how much the power source could be relied upon (Monk et al., 2009). A total of 8200 feasible project sites were identified across BC using the following selection criteria: discharge between 0.1 and 200m³/s, hydraulic head between 30 and 1000m, in-stream power greater than or equal to 500kW, and a set of practical selection criteria (e.g., park boundaries, protected fish habitats, etc.). The model was validated against the Water Survey of Canada discharge measurements; however, the results of this validation and the associated uncertainty in the power estimates were not provided. The model also calculated the capital cost of extracting HKE at each location using the best route to the accessible roads, transmission lines, etc. which were optimized by RHAM (Kerr Wood Leidal Associates, 2008; Monk et al., 2009).

The Electric Power Research Institute (EPRI) (Jacobson, 2012) was commissioned by the U.S. DOE to provide an estimate of total riverine HKE in the US and the resulting report was published in 2012. The study predicted two estimates of HKE: theoretically available power and technically available power. The theoretically available power was calculated similarly to the hydropower Equation 2-4 and the technically available power was calculated similarly to the HKE Equation 2-1 in addition to utilizing a recovery factor. For the theoretically available power, data were taken from the NHDPlus database, which is a GIS database containing discharge and channel slope information for river segments. Only the largest US rivers were used in the assessment initially, with the constraint of discharges greater than 283m³/s. The assessment was then expanded to rivers between 28.3m³/s to 283m³/s (1,000cfs to 10,000cfs). The report does not specify what type of discharge this is (i.e., mean annual discharge, 25 percentile

discharge, etc.). The HEC-RAS model was employed to simulate average velocity at 5 different discharges: 5, 25, 50, 75, and 95 percentiles. A V-shaped channel was assumed when using the HEC-RAS model, and the effects of introducing the turbine into the river were considered in the HEC-RAS model. The recovery factor applied to calculate the technically available power was derived from the following data at five gauged sites: minimum required water velocity and depth during low discharge, device efficiency, and discharge statistics. Rivers with hydroelectric dams were excluded from the analysis at this point. From the analysis, it was found that the recovery factor decreased with increasing discharge. Application of the recovery factor decreased the theoretically available HKE of 1,381TWh/year to the technically available HKE of 119.9 TWh/year. A section of the report was dedicated to explaining and quantifying the uncertainty in the final results. Uncertainties were propagated from the slope and discharge data in the theoretical power result. The NHDPlus database used for slope values was compared to an alternative source (Google Earth or Wikipedia), and the comparison showed small uncertainties when considering the slope of the entire river. However, when smaller segments were analyzed, larger uncertainties were present. Discharge data in the NHDPlus database was compared to USGS discharges, and it was concluded that the differences contributed little to the overall uncertainty in the final power estimates. Uncertainties in the technical estimates were the result of assuming a V-shaped channel and a normalized flow distribution curve based solely on discharge statistics at one location on the Mississippi River. Uncertainties or deviations were represented either by % deviation or by R^2 . A sensitivity analysis was also completed to determine the influence of various factors on the recovery factor (Jacobson, 2012).

In 2013, the National Research Council (NRC) of the National Academies (2013) published an evaluation of the EPRI's assessment and associated recommendations for improving such assessments in the future. To begin, the NRC Assessment Committee created the conceptual framework of the difference between a theoretical resource, a technical resource, and a practical resource. This differentiation is also seen in the IEC standards where theoretical resource assessments are concerned with the idealized amount of HKE that can be extracted with all factors outside of the available energy resource not considered; technical resource assessments consider the limitations of HKE extraction technology; and practical resource assessments take into account the real-world societal, environmental, economic constraints (IEC, 2019). The NRC argued that the EPRI (2012) study did not put proper emphasis on the practical resource aspect of the project, because the practical estimate would better represent realistic constraints to HKE technology development and deployment. The NRC also presented a strong reservation to providing a single-number HKE estimate for the whole nation or for a large geographic region. The reason for this is that it does not lead to a realistic discussion when comparing HKE to other energy options, as it is usually intended to do. Additionally, because of the high level of uncertainty in the assessment, the resulting value obtained

is not defensible. Another critique of the EPRI (2012) study was that the all-encompassing project proposed by the U.S. DOE to estimate all marine and HKE in the U.S. was split into five groups with little coordination and consistency among them in terms of methodology, validation, and deliverables. The third criticism was that not enough emphasis was put upon the device installation feedback on the environment in the analysis, as well as lack of or inconsistent validation and quantification of uncertainties in the estimates. Because the EPRI (2012) assessment also attempted to estimate technically available power, the NRC recommended to focus the analysis on locations that were most likely to provide most of the potential HKE and improve the assessment there, and to employ a two- or three-dimensional model to evaluate the turbine's effect on the river environment and discharge. Finally, the NRC recommended a stronger consideration of statistical variation of river discharge by utilizing discharge statistics for each segment. The NRC also recognized that modelling the river's discharge is complex and difficult when a turbine is introduced (National Research Council, 2013).

Jakimavičius et al. (2014) conducted a large-scale study on 282 small and medium sized rivers in Lithuania where equations similar to those of hydraulic geometry (see Equations 2-16 to 2-20 in Section 2.4) were used and the equation parameters were estimated to estimate channel geometry and flow velocity. The equations parameters were estimated using hydromorphological equation exponents compiled by Gailiusis et al. (2001). Using the estimates of velocity and water depth obtained via the equations, the channels available for energy extraction were filtered using depth and velocity constraints of greater than 0.5m and greater than 0.4m/s, respectively. This reduced the number of channels considered in the assessment to 41. HKE was calculated using the hydropower Equation 2-9 with the hydraulic head being the change in surface elevation over the river segment and the flow being the average multiannual discharge. The velocity, depth, and width equations used to constrain the number of channels used in the assessment were validated against data of 14 channels of various sizes which were not used in the original generation of the equations. The validation resulted in average relative errors of 14.0%, 17.9%, and 19.0% for depth, width, and velocity, respectively (Jakimavičius et al., 2014).

To the authors' knowledge, one of the most recent extensive HKE assessments was completed by Jenkinson and Bomhof (2014) for the National Research Council (NRC) of Canada in 2014. This study utilized a regionalization approach to estimate discharge statistics for all river segments in Canada – gauged and ungauged – that could be analyzed. To begin, the drainage basins for each river segment in consideration were delineated using Voronoi tessellation. Then, to estimate discharge, the regionalization approach used was multiple linear regression coupled with canonical correlation analysis. This method was used under the assumption that streams across Canada in watersheds of similar physiographic characteristics would behave similarly. For example, the method

would assume watersheds with particular ratios of landcover classes would behave hydrologically similarly to those with similar ratios. Discharge data were obtained from the Water Survey of Canada. The outputs of the regionalization were 17-point evenly distributed FDC for each stream segment. HG principles and another regionalization were used to estimate width and depth of river segments along each point of the FDC. The Water Survey of Canada – Measurement Database provided the channel geometry data for the analysis. Uncertainty was quantified using a Monte Carlo technique that represented the uncertainty with a distribution of discharges that corresponded with the distribution of the discharge estimate's uncertainty. Both the theoretical hydropower and the HKE were calculated in their analysis using the following two equations:

$$[2-11] P_H = \gamma H \int_0^1 Q(f_Q) df_Q$$

And

$$[2-12] P_K = \gamma L n_M^2 \int_0^1 \frac{Q(f_Q)^3}{w(f_Q)^2 d(f_Q)^2 [2d(f_Q) + w(f_Q)]^{4/3}} df_Q$$

where L is the length of the river segment, n_M is the Manning's roughness coefficient, and $Q(f_Q)$, $w(f_Q)$, and $d(f_Q)$ are the river discharge, flow width, and flow depth corresponding to the flow frequency, f_Q , respectively. Equation 2-12 was derived using Equation 2-1 and Manning's equation. However, if this method were to be used in the future, the following equation should be used, as an error exists in Equation 2-12 where the wetted perimeter was used instead of the hydraulic radius for R .

$$[2-13] P_K = \gamma L n_M^2 \int_0^1 \frac{Q(f_Q)^3 [2d(f_Q) + w(f_Q)]^{4/3}}{[w(f_Q) d(f_Q)]^{8/3}} df_Q$$

The resulting theoretical HKE estimates for the Jenkinson and Bomhof (2014) study were 711GW with 97.5% confidence that at least 433GW was available for hydropower and 343GW with 97.5% confidence that at least 29GW was available. The study, however, contained limitations. Uncertainties were properly considered in the final results, but this led to a wide range of possible values and ultimately showcased the imprecision in the data and regional analysis methods. The analysis was also not able to include the far north of Canada because of data limitations. Digital elevation model (DEM) resolution was limited at the time of analysis; thus, the river segment slope was calculated using elevation at the beginning and end points of the segment. This method of assuming a uniform slope would not have captured non-uniform elevation drops caused by falls, rapids, rocks, etc. Additionally, the HG method of estimating channel width and depth could not capture abnormalities in channel shape. This is of particular interest as channel constrictions could cause favorable conditions for high velocity and high HKE potential. Finally, validation with data collected via a field campaign was performed for this assessment (Jenkinson and Bomhof, 2014).

Cruz et al. (2020) developed a numerical model called the flow-velocity model that estimates daily average velocity and distribution of velocity across a transect of the channel using flow data. This study estimated the HKE potential of all rivers in the Amazon Basin. To calibrate the model, parameters were optimized so that the simulated flow rate compared to the observed flow rate contained less than 10% relative error. The output of the model was velocity isolines across the cross section of interest. Validation was conducted with observed flows and velocities at 3 gauging stations. The validation resulted in average errors of 3.07% and 3.13% for the flow and the velocity, respectively. This study took the Betz limit (i.e., $C_p = 0.593$) and a more conservative C_p of 0.25, recommended by Vermaak et al. (2014), into consideration when calculating estimates of HKE potential (Cruz et al., 2020).

As shown in the progression of the HKE assessments from 1980 to 2020, it seems that the methods used to estimate HKE on the regional have become more complex with increasing understanding of the factors that affect the amount of HKE available. For example, models were utilized more often as the influence of two- and three-dimensional flow was understood, and discharge statistics were employed in the later studies as non-stationary climate was considered. It is difficult to conclude for certain, as documentation was scarce for some studies, but it appears that the consideration of variability of discharge increased gradually, with the first studies not taking it into consideration; the next generation of studies considering low, mean, and high discharges; and the later generation of studies utilizing a FDC or daily flow data to characterize the discharge variability. Also, data processing techniques changed as computational power increased, allowing for the use of complex numerical modelling and GIS techniques. In addition to the tools for HKE assessments becoming more sophisticated, the resolution, amount, and quality of the data available for the assessments increased. Even now, DEM data are of higher resolution in some areas of Canada (i.e., Arctic and New Brunswick) than it was during Jenkinson and Bomhof's (2014) assessment. Documentation and reporting of the techniques used in the assessments also seems to have improved as time went on, with the most recent studies not only being publicly available for evaluation, but also the content and explanation in the reports was of higher quality. As far as evaluation of the results of the HKE assessments, the procedures for validation and quantification of uncertainty were not consistent. Development of standard approaches for validation and uncertainty assessment would improve regional HKE assessments. Providing a singular, comparable measure of the success of the method would improve these types of studies, as the most suitable and accurate methodology could be chosen to be employed in the future. Finally, as the NRC (2013) suggested in their evaluation of the EPRI's (2012) report, more emphasis could be placed on practical and technical availability of HKE potential, rather than theoretical potential, as those two types of assessments would provide more value to the field of HKE evaluation. However, this is not to say that theoretical assessments should not be completed in the future. In the Jenkinson and

Bomhof (2014) assessment, only theoretical HKE potential was considered; however, the data and techniques used in the assessment and the scope of the study were novel at the time. Therefore, until the methodology and data required for these types of regional assessments are common enough to be standardized (as with local assessments), conducting regional theoretical assessments of HKE potential are useful and essential.

As shown in local HKE studies in Section 2.2, sometimes sufficient discharge, bathymetry, or velocity data are not available for the location of interest to be able to calculate HKE from Equation 2-1 or Equation 2-2. This issue is amplified when regional assessments are attempted. For example, the required velocity data are rarely already available at the location of interest or at the resolution required without a field-testing campaign. As per the IEC standards, even if numerical modelling is employed to simulate the velocity profile, two cross sections of velocity are required for validation. These data are not usually available in regional studies. Additionally, when attempting to estimate HKE at a regional scale, generally all rivers in the region are considered for analysis to detect the optimal reaches for HKE extraction. Rarely will all rivers and streams be properly gauged within a region, let alone contain ten or more years of discharge data. As per the IEC standards, the ten years of required discharge data can be simulated through modelling, but the data must be validated with one year of discharge data. The one year of discharge data may not be available for regional assessments, if one wishes to consider the HKE potential of all reaches within a region. Because of time and expense constraints, accurate bathymetry data cannot be obtained via field measurements. As such, methods to estimate the bathymetry must be utilized to assess HKE in regional studies. If the locations of interest within the assessment region have depth and width measurements, a channel shape can be assumed (e.g., parabolic, trapezoidal, rectangular, etc.), and an approximate bathymetry can be obtained. However, reaches within the regional assessment may not have width or depth measurements, and they must be obtained or estimated through other means. Even if the data and methods are available to model the discharge, velocity, or bathymetry of the reaches within the regional assessment region, computational requirements may limit the use of those data and methods to local assessments. As such, a compromise must be struck between the amount and resolution of data available, computational requirements of manipulating the data, and the intent of the regional assessment. Generally, the purpose behind the regional assessment is not the same as the local. Regional studies are a type of pre-reconnaissance study to locate areas of interest that may contain promising HKE potential in order to conduct a concentrated local assessment. Therefore, one must keep the methods of local assessments in mind but also do what is possible with the data and techniques available at the regional scale.

Limitations of regional types of HKE assessments generally present themselves as some sort of threshold factor of the river for which HKE estimates cannot be calculated

or uncertainty limitations in the methods currently available. Regional assessments are always limited by some sort of threshold, and this threshold is determined by the amount, quality, and data available. For example, in Jenkinson and Bomhof's (2014) study, the far north of Canada could not be assessed because there were insufficient data to properly characterize the discharge in those regions. Additionally, the scopes of most of the earlier studies were limited by some threshold discharge, velocity, or channel geometry; however, information was not available for the reasoning behind these thresholds in the study reports, so it is not known if the thresholds were introduced due to data limitations, computational limitations, or practical reasons (e.g., low HKE potential below some threshold discharge). Another current limitation of regional HKE assessments is the uncertainty associated with the current methods. As shown by Jenkinson and Bomhof (2014) in their final hydropower and HKE estimates and the associated uncertainties, great unreliability lies in the current methods of assessing HKE potential to provide a single value of all HKE available in Canada. However, this uncertainty may be smaller for individual river reaches, which, as the NRC (2013) states, is the more relevant scale.

2.4 New Techniques/Technologies

For regional assessments, either an equation similar to Equation 2-1 can be used to calculate HKE or an equation similar to Equation 2-9 can be used to calculate hydropower. As both equations require different inputs, the section herein will cover new techniques or technologies that may yield more effective estimates of all of the equations' inputs. For hydropower estimation, the inputs are hydraulic head (i.e., slope or elevations) and river discharge. For HKE estimation, the inputs are velocity and cross-sectional area. If the HKE density equation is used (Equation 2-2), then only velocity is needed. To estimate velocity within the river, either the continuity equation or Manning's equation can be used, both of which are shown below, respectively:

$$[2-14] \ v = \frac{Q}{A} = \frac{Q}{wd}$$

And

$$[2-15] \ v = k_M R^{2/3} S^{1/2} / n_M$$

where w is channel width, d is channel depth, k_M is the unit conversion factor ($k = 1$ for SI units and $k = 1.49$ for English units), R is the hydraulic radius (flow area divided by wetted perimeter), and S is the slope (i.e., elevation and segment length). For either method of calculating velocity, width and depth are needed. For the continuity equation, river discharge is required and for Manning's equation, slope and roughness are required. These methods of calculating hydropower or HKE are purely theoretical and can be converted to technical or practical estimates by introducing a power coefficient or other

factor to account for the turbine characteristics and by considering factors which may affect the feasibility of successful deployment (e.g., protected areas, proximity to communities or transmission lines, ease of access, etc.). As the conversion of theoretical HKE to technical or practical is circumstantial, only technologies and methods that may improve theoretical assessments will be discussed here.

2.4.1 Discharge

Recent developments in river discharge estimation methods and technologies are explored. Remote sensing methods of estimating discharge have been of particular interest, especially for rivers with no gauging stations and in remote areas where it would be expensive and restrictive to launch a field work campaign. These remote sensing techniques are not nearly accurate enough to replace a field campaign; therefore, use is dependent on the level of accuracy required for the assessment. Satellite techniques have gained much attention since the National Aeronautics and Space Administration (NASA) Surface Water and Ocean Topography mission (SWOT) was announced. The mission is set to launch in September 2021 (NASA, 2022) and its applications reach far beyond river discharge estimation (Pavelsky, 2019). Since the announcement of the data that will be available from the SWOT satellite mission, hydrologists have begun developing various methods to utilize the data to estimate river discharge, sometimes in combination with other data (i.e., gauged data from other areas, historical HG relationships, DEMs).

Gleason and Smith (2014) conducted a study in 2014 to test their proposed at-a-many-station HG (AMHG) method, when they realized a relationship existed between the coefficients and the exponents of traditional HG equations as will be explained below. Typical HG relationships are shown below:

$$[2-16] \ w = aQ^b$$

$$[2-17] \ d = cQ^f$$

$$[2-18] \ v = kQ^m$$

Where a , c , and k are the calibrated coefficients and b , f , and m are the calibrated exponents of the relationships, and:

$$[2-19] \ ack = 1$$

$$[2-20] \ b + f + m = 1$$

HG relationship data from 88 USGS gauging stations across 6 rivers throughout the U.S. were used to plot the exponents (b , f , and m) against the coefficients (a , c , and k) of the relationships for each river, a strong log-linear relationship was found. For example, for a 428 km stretch of the Chattahoochee River that contained 13 gauging stations with available HG relationships, b was plotted against $\log(a)$ and resulted in a linear

relationship with an R^2 of 0.80. Therefore, it was concluded that only one calibration parameter was needed for the width-discharge relationship at rivers where strong at-a-station hydraulic geometry existed. Gleason and Smith (2014) then compared the log-linear AMHG relationship between discharges and widths derived from HEC-RAS hydrodynamic model versus discharges derived from in-situ measurements and widths extracted from LANDSAT data. This was completed across 3 different rivers for each scenario: Rio Grande, Mississippi, and Sacramento Rivers for the modelling approach and Athabasca, Mississippi, and Yangtze Rivers for the remote sensing approach. Gleason and Smith (2014) found strong conformities between the results from the in-situ method versus the results from the remotely sensed width. Root mean squared error (RMSE) was used to quantify the errors in the proposed method. When comparing discharge measurements to the discharges estimated by the AMHG method, RMSEs were 23%, 30%, and 20% for the Mississippi, Athabasca, and Yangtze Rivers, respectively. When comparing the discharge estimations obtained from the HEC-RAS model versus discharge estimated by the AMHG method, RMSEs were 27%, 26%, and 1083% for the Mississippi, Sacramento, and Rio Grande Rivers, respectively (Gleason and Smith, 2014).

Liu et al. (2015) proposed a method in 2015 that utilized both the Soil and Water Assessment Tool (SWAT) hydrologic model and the XSECT hydraulic model in a looping algorithm to calibrate parameters and converge on the final estimates of water depth and discharge. Both altimetry data and optical imagery were used from ENVISAT and LANDSAT, respectively, to calibrate the parameters using water level and channel width. The method was evaluated on the Red River and, when the resulting discharge was compared to measured discharge, yielded R^2 values of 0.822 and 0.924 for daily and monthly discharge estimates. The analysis was expanded to the tributaries of the Red River and the resulting average R^2 of those discharge estimates was 0.809 over seven different gauge stations. As for water depth estimates, when compared to depth measurements, the average R^2 was 0.831. Liu et al. (2015) found that the limitation to the success of this method was the resolution of available data.

Sichangi et al. (2016) conducted a study in 2016 on eight major rivers with channel widths greater than 800m (Mississippi, Yangtze, Congo, Danube, Volga, Amazon, Lena, and Yenisey), and utilized satellite altimetry data, optical imagery, and DEMs to calibrate parameters in a modified Manning's equation to estimate discharge remotely. The altimetry data used was from multiple sources, including ERS-1, Topex/Poseidon, ERS-2, GEOSAT Follow-On, Jason-1, and ENVISAT and was used to create a water level time series. The optical imagery came from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite (250m resolution) and was used to determine channel width. MODIS images were chosen for their high temporal resolution in order to correlate the date of the altimetry data to the optical imagery. The average relative error

associated with the channel widths derived from satellite imagery was 9.48%, and the width uncertainty was less in smaller rivers (i.e., less discharge) compared to that of larger rivers. Sichangi et al. (2016) acknowledged that this error could be improved with using high spatial resolution satellite imagery. From the derived water level time series, estimated channel widths, and elevation data from the DEMs, the parameters in the modified Manning's equation were calibrated and the resulting discharges calculated had a Nash-Sutcliffe (NS) efficiency between 0.60 and 0.97. Sichangi et al. (2016) also considered two different models: one which assumed that very large rivers had a constant width, where Q was proportional to $d^{5/3}$, and another where Q was proportional to $w \times d^{5/3}$. In general, the second model performed marginally better (NS of 0.60 versus 0.52, relative RMSE (RRMSE) of 25.5% versus 27.8%, relative error of 7.07% versus 7.57%, and R^2 of 0.64 versus 0.56 for the Yangtze River) (Sichangi et al., 2016).

2.4.2 Channel Width and Depth

In past regional HKE studies, channel dimensions were obtained either by direct measurements available through some regional or national database or by hydraulic geometry relationships and principles. However, these techniques can only be used if high quality, extensive data are available for a region. It is also important to note that, as well as spatial coverage, the data used for a regional HKE assessment must have adequate temporal coverage. Because river discharge fluctuates, width-discharge and depth-discharge curves are required to properly characterize the variation in river conditions and, by association, the variation of potential HKE. New techniques, as shown above in the discharge section, have utilized remote sensing technologies to derive channel width to estimate discharge. Therefore, these same techniques could be promising for estimating channel width when calculating velocity using Equation 2-14. On the other hand, methods of estimating channel depth from remote sensing techniques do exist but contain much error and uncertainty, as will be shown below. Sampson et al. (2015) made the argument that "river depth is the most difficult parameter to estimate as it is not yet possible to measure this remotely on large scales".

Generally, the method of determining channel width from optical imagery is split into two steps: water mask generation and derivation of widths from the mask. The first step is required to extract channel centerlines and widths using automated or semi-automated methods, which is desirable for regional assessments. What is meant by a water mask is generating an alternative image from the source image where the pixels are of only two values: water and non-water. This can also be called image segmentation. The steps required for successful creation of the water mask depend on the type of imagery that is available for manipulation. All imagery must first be orthorectified and geo-referenced in order to properly and accurately measure channel width (Ansari et al., 2017). The amount of noise, unwanted objects (e.g., clouds or other bodies of water), and required atmospheric correcting in the images must be considered in pre- and post-

processing steps (Ansari et al., 2017; Bolanos et al., 2016; Brisco et al., 2009; Elmi et al., 2016; Li and Sheng, 2012; O'Loughlin et al., 2013). Some pre-processing that can be applied to avoid inaccurate segmentation are initial thresholding, initial differentiation (e.g., employing DEMs to exclude areas of high slope), adjusting sharpness or blur, applying a Normalized Difference Vegetation Index, or applying a variety of other filters to optimize the difference between water and land pixel intensity (Ansari et al., 2017; Bolanos et al., 2016; O'Loughlin et al., 2013). Generally, images are also converted to greyscale and pixels are converted from intensity to decibel scale. After pre-processing, a segmentation method can be applied to differentiate the land pixels from the water pixels. The most common method of image segmentation is thresholding, where a threshold value, for which above or below pixels are designated as water, is chosen automatically. Some techniques that automatically select thresholds for this type of work are ISODATA, Mean, Maximum Entropy, Minimum Error, Moments, and Otsu (Glasbey, 1993; Kapur et al., 1985; Kittler and Illingworth, 1986; Otsu, 1979; Ridler and Calvard, 1978; Tsai, 1985). Post-processing can also take place to refine the segmentation method's selections, such as disregarding lakes or glaciers.

After the water mask has been generated, the channel widths can be extracted using channel centerlines that are generally also generated as an intermediate step. The most common algorithm used to derive channel widths, at least in North America, is RivWidth (Allen and Pavelsky, 2015; Durand et al., 2010; Pavelsky and Smith, 2008). The software was developed by Pavelsky and Smith (2008) and requires two input images to calculate channel widths at set intervals: the binary image with mid-channel land (e.g., sand bars or islands) included as land pixels and another binary image with mid-channel land not differentiated from the water it is surrounded by. However, O'Loughlin et al. (2013) argued that RivWidth created overlapping cross-sections where the channel turned at a sharp angle, and this introduced error into the channel widths. Other methods exist to derive channels widths, such as the methods by Sofia et al. (2015), O'Loughlin et al. (2013), and Yamazaki et al. (2014). Sofia et al. (2015) calculated channel width from a 1m resolution LiDAR digital terrain model (DTM) using a quantile-quantile plot statistical approach. Bankfull width is assumed to be where the Q-Q plot deviates from normality. This method was used to calculate reach-averaged width; however, the approach may not be sufficient to capture sudden constrictions in the channel. As mentioned before, O'Loughlin et al. (2013) had criticisms of RivWidth and, to correct the overlapping cross sections, employed a semi-automated method of developing orthogonals in HEC-GeoRAS to manually correct the errors. Yamazaki et al. (2014) used an existing dataset of water polygons called the Shuttle Radar Topography Mission Water Body Data to extract channel width using an algorithm that determined the centerline using the bank pixels and generated the discharge direction to the centerline. To work with the dataset, the method also required an algorithm to fill gaps in the water polygons. Using this

method, Yamazaki et al. (2014) developed the Global Width Dataset for Large Rivers between 60°N and 60°S.

As mentioned previously, compared to channel width, channel depth estimation via remote sensing methods is more difficult and contains more uncertainty. The feasibility of utilizing the methods that will be mentioned depend on the type of data available across the region of interest (e.g., optical imagery versus altimetry data), the resolution of the available data, and the study location itself. As with channel width estimation, depth estimation generally consists of two steps: obtaining a water surface elevation dataset that is generated from altimetry or DEMs and estimating the channel depth using the water level time series and the proposed method. The method of depth estimation by Liu et al. (2015), mentioned previously in the discharge section, used a looping algorithm with two models – XSECT and SWAT – to optimize parameters and converge on discharge and channel depth estimates. This method used water level time series from altimetry data and channel widths derived from optical imagery. The technique performed fairly well with an average R^2 of 0.831 when comparing derived channel depths to measured depths. Durand et al. (2014) utilized an algorithm based on Manning's equation to estimate channel depth and discharge using a pixel grid of synthetic SWOT measurements. The simulated water surface elevation data, intended to represent future SWOT data, was generated from an instrument measurement model and the hydrodynamic model LISFLOOD-FP. The purpose of Durand et al.'s (2014) study was to prepare a method of deriving channel depth and discharge from SWOT data before the SWOT data became available. This method required good temporal coverage of data; however, it can be argued that all channel depth estimation methods would require good temporal coverage of data for accurate estimates. Schaperow et al. (2019) proposed a method that built off of Mersel et al.'s (2013) work where water level data and channel width were essentially extrapolated to a zero water level condition using a number of relationships. The relationships proposed by Mersel et al. (2013) were linear and slope break and the relationships proposed by Schaperow et al. (2019) were non-linear and non-linear slope break. Better results were observed when more data coverage was available at different discharge conditions (i.e., capturing many different high and low discharges). The method resulted in a relative error of -3.1% for non-linear slope break and -7.1% for non-linear (Schaperow et al., 2019). Tourian et al. (2017) employed a method where, instead of extrapolating to a zero water level condition, a modified Manning's equation was used and the Gauss-Helmert Model (Helmert, 1872) was applied. This method resulted in an estimate of the channel depth and the associated error when the parameters were converged upon in the iterative algorithm used, and the resulting average RRMSE was 10% (Tourian et al., 2017). Again, success of the method depended on coverage and availability of the source data (Tourian et al., 2017). In general, for successful estimate of channel depth from remote sensing methods, good temporal coverage of available data is needed. However, to support regional HKE

assessments, the type of data (i.e., altimetry or elevation), the resolution of the data, and the amount of data needed are not currently available. In the future, the NASA SWOT mission may fill these needs and make estimation of channel depth from space possible.

2.4.3 Channel Slope

To improve estimates of channel slope to support more accurate calculations of hydropower using Equation 2-9, new methods that require higher resolution DEMs or DTMs could be employed. In Canada particularly, with new data generation initiatives being launched nationally, provincially, and privately, a 1m resolution LiDAR DTM is available in New Brunswick and 2m digital surface models (DSMs) are available in the Canadian Arctic (north of 60°N) via ArcticDEM. With these types of high resolution DTMs or DSMs, the channel can be represented as a number of elevation changes, rather than one elevation change between the points of interest and averaging the slope across that length (Allen et al., 2013). Allen et al. (2013) employed such a method which stretched DEMs and assigned an elevation to each centerline pixel along a meandering river using a 90m resolution DEM and 5m resolution optical imagery. They found that the represented channel profile more closely resembled the GPS field measurements, and the gradient was corrected by -12.6% when employing this method compared to a traditional method of gradients only from DEMs (Allen et al., 2013).

2.4.4 Roughness

The flow resistance coefficient (e.g., Manning's roughness n in Eq 2-9) is usually assumed to be a constant value in regional HKE studies (e.g., Jenkinson and Bomhof (2014)). To improve the estimation of regional roughness values, regionalized relationships between roughness and other measurable factors – discharge, slope, surficial geology, channel bed substrate D50 – could be explored, developed, and used to estimate bed and bank roughness. Two studies of natural river roughness were examined herein for relationships between roughness and the aforementioned factors. These studies were by Barnes (1967) for U.S. rivers and by Hicks and Mason (1998) for New Zealand rivers. From the Barnes (1967) data set, a relationship was found to exist between slope and roughness for rivers located in the U.S. Western Cordillera with an R^2 of 0.694. This suggests that a site-specific roughness estimate can be assigned to a river reach if the appropriate data are available and a strong relationship between roughness and other measurable factors can be identified. However, no other significant relationships were found between roughness and other measurable factors in the Barnes (1967) and the Hicks and Mason (1998) data. Thus, in future regional HKE assessments, roughness will likely continue to be assigned a constant mean or typical value in areas of poor or no relationships between roughness and other factors.

2.4.5 Other Possible Methods

Other available data could possibly be utilized for these types of regional HKE assessments, depending on the data available in the region. For example, d'Auteuil et al.

(2019) explored the relationship between open water on rivers during winter and high velocity conditions using satellite imagery and field measurement campaigns. The idea was that if high velocity, and therefore high potential HKE, could be located using winter imagery, project developers could use that information to invest more into a particular location (d'Auteuil et al., 2019). However, as it seems, this method could not be used to estimate the amount of HKE available, only that the location has the potential for extractable HKE. Also available in Canada is NRCan's CanVec dataset which contains polygons for locations of rocks, rapids, falls, and other hydro obstacles within river channels where high velocities are more likely to exist. This dataset could possibly be used to focus HKE assessments to reduce computational limitations. For example, computing channel gradient for all rivers in an entire country would be exceedingly computationally expensive, but if channel gradients were to be calculated only at the reaches for which a hydro obstacle occurs, the data would be more manageable. Also available through the NRCan's CanVec database are waterbody extent polygons which could be used for either preliminary or final determination of channel width, depending on the accuracy of the polygons' representation of channel shape. Other types of useful datasets could be available nationally or regionally for various nations around the world to aid in conducting these types of HKE assessments.

2.5 Review and Research Needs

When comparing the methods used to complete local HKE assessments to regional assessments, one finds that local methods cannot be replicated in regional studies and must be modified to suit computational and data limitations, particularly in the utilization of models. The discharge, bathymetry or stage, and velocity measurement data required for the IEC standards are not available at the regional scale if one desires to consider and estimate the HKE potential in all rivers. Therefore, in the past, regional assessments have been limited to gauged river segments (Jacobson, 2012; Kerr Wood Leidal Associates, 2008; Miller et al., 1986; Monk et al., 2009; UMA Group, 1980). However, newer techniques have allowed for estimation of ungauged river characteristics using techniques such as regionalization and discharge modelling (Jenkinson and Bomhof, 2014; U.S. Department of Energy, 2004). To combat the lack of data related to channel dimensions, and therefore mean velocity, authors of regional assessments have sometimes relied on the calculation of hydropower rather than HKE because the data were readily available (i.e., DEMs and discharge data).

To improve HKE assessments, there are many steps that can be taken. For local assessments, researchers should follow the specifications set out by the IEC (2019) and only deviate when necessary with reasoning given. For regional assessments, the steps and ideology behind the IEC standards (2019) should be followed as closely as possible, but methods will be needed to generate the required data. To improve regional HKE

studies, uncertainty or error analysis should be more consistent and consideration should be taken towards the technical and practical applications of the generated data. The following aspects should always be considered in, if not introduced into the methodology of, regional assessments: discharge statistics, implications of complex flow, and climate change impacts. To improve these assessments, documentation should become more standardized, and as new data become available from various initiatives (e.g., SWOT, LiDAR DTMs, altimetry data, new satellite missions, etc.), assessments should be revisited to improve previous estimates.

The use of remote sensing techniques for aiding in these types of assessments should be thoroughly investigated. The capabilities of SWOT data, as well as other high resolution satellite products, should be tested to estimate hydrokinetic energy when it becomes available for research efforts. In particular, the methods used by Durand et al. (2014), Elmi et al. (2016), Tourian et al. (2017), and Schaperow et al. (2019), which were used to estimate channel geometry (depth and width) and discharge, are attractive to use for hydrokinetic energy estimation. With increased quantity and resolution of remotely sensed data, the aforementioned techniques, particularly the estimation of channel depth and discharge, will become more feasible and the accuracy of the results will improve. In addition to newly available remotely sensed data and techniques, alternative datasets available for the study region could be considered for their use in regional HKE assessments. These datasets could possibly concentrate efforts in the assessment to areas of higher likelihood of high HKE potential or feasibility, or even aid in preliminary or final determination of channel features to guide identification of optimal HKE installation locations.

2.6 Conclusions

HKE extraction could provide a promising future for alternative electricity generation to facilitate the transition from fossil fuel sources in Canada and around the world. Regional theoretical, technical, and practical HKE assessments are essential for understanding the feasibility of extracting and relying on this type of electricity in the future, as well as providing data to developers. To complete these assessments, a general trend involving the transition of manually manipulating relatively small amounts of available data to utilizing GIS, statistical, and modelling techniques to manipulate and generate new data (e.g., discharge, velocity, channel dimensions, etc.). In the most recent regional HKE assessments, the influence of discharge variation was appropriately considered, and the uncertainty of the estimation method was properly characterized, which is an improvement from previous studies and consistent with the IEC standards (IEC, 2019; Jenkinson and Bomhof, 2014). Since this study, researchers have explored utilizing remote sensing methods to estimate channel features with varying success. The most successful methods are concerned with estimating channel width, whereas

estimation of channel depth is still difficult to accomplish from space. As the resolution and quantity of the available remotely sensed data increases, the presented methods will become more feasible to accurately estimate channel features. Other available relevant datasets for the region of interest should be explored thoroughly for use in the regional assessments. Because the type and amount of data is inconsistent across regions (e.g., in Canada, LiDAR is only available north of 60°N and in New Brunswick), the methods of regional HKE assessments may never be as uniform as local assessments. However, as new methods are developed to estimate channel characteristics for regional HKE assessments, the IEC standards for local HKE assessments should be considered. For example, the influence of discharge variation, quantification of uncertainty or error, and possible utilization of models should always be considered in any type of HKE assessment.

Chapter 3. Local Hydrokinetic Energy Resource Assessment Case Study

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Rennie, C.D., Cousineau, J., Ferguson, S., Nistor, I., 2023. Impacts of seasonal flow variation on riverine hydrokinetic energy resources and optimal turbine location – Case study on the Rivière Rouge, Québec, Canada. *Renew. Energy* 210, 364–374.

Abstract:

Hydrokinetic energy resource assessment is a crucial prerequisite for strategic turbine deployment and energy extraction. Despite advancements in analytical tools, resource assessment is often completed without detailed investigation of spatial and temporal flow variation and implications on optimal turbine placement. A case study was conducted on the Rivière Rouge, Québec, Canada to estimate the hydrokinetic energy resource, to locate the optimal turbine placement, and to study the impact of seasonal flow variation. The primary optimal turbine location did not change, but the second, third, and fourth optimal locations were impacted. Assuming a hypothetical deployment of one turbine with a 1 m² swept area, the theoretical hydrokinetic energy resource for the site was 21.8 MWh per year in the optimal turbine locations and 6.2 MWh per year using the reach-averaged velocity. This difference illustrates the need to consider the entire velocity flow field in hydrokinetic energy assessments. To conduct the assessment, field data were collected with an acoustic Doppler current profiler and a global positioning system for hydrodynamic model generation, calibration, and validation using the software TELEMAC-2D. The mean absolute percentage errors of the model in the areas of interest were 14.8% for calibration and 22.9% and 19.4% for validation.

Keywords: Hydrokinetic energy resource assessment; hydrodynamic model; optimal turbine placement; acoustic Doppler current profiler; river hydraulics; seasonal flow variation

3.1 Introduction

Hydrokinetic energy may prove to be one of the solutions to Earth's greenhouse gas emission problems. It utilizes the natural flow of a river to turn a hydrokinetic turbine to generate electricity. The turbine converts the flow into electrical power via a generator and other electromagnetic equipment. Unlike conventional hydropower, hydrokinetic energy extraction does not significantly alter the flow pattern of the existing river, as it does not require damming of the flow. As such, the negative ecological, environmental,

and societal impacts of conventional hydropower, such as degradation of fish passage, water quality, and aquatic and terrestrial habitat concerns (Batalla et al., 2021; Cada et al., 2007), can be avoided while still utilizing the renewable energy of running water. These advantages have inspired increasing research interest focused on developing and refining techniques to assess and quantify hydrokinetic energy resources. However, it is important to note that conventional hydropower is generally more efficient and readily available when compared to hydrokinetic power. Because hydrokinetic applications do not dam the river flow, the natural fluctuations of the river heavily influence the amount of energy available for extraction. Additionally, the method of energy extraction is less efficient, with a maximum efficiency limit of 59.3% in unconstrained flow, known as the Betz limit (Yuce and Muratoglu, 2015). The actual efficiency that can be achieved in full-scale deployment is further impacted by complex flow structures, as well as practical constraints and technical limitations. Past, large-scale resource assessments have estimated theoretical hydrokinetic energy resources equal to 100TWh annually in the Continental U.S. (U.S. Department of Energy (DOE), 2015) and 340 GW (3000 TWh annually) in Canada, with a lower prediction of 29 GW (250 TWh annually) (Jenkinson and Bomhof, 2014). The theoretical amount of hydrokinetic energy present in a river reach is proportional to the cube of the flow velocity, as shown in Equation 2-21 below:

$$[3-1] P_K = 1/2 \rho A v^3$$

Where P_K is the kinetic power (i.e., hydrokinetic power), ρ is the density of the water, A is the swept area of the turbine (assumed to be 1 m² in this study), and v is the flow velocity. Flow velocity is the most influential factor affecting hydrokinetic power availability. Because of this, and also because the flow velocity varies greatly through a river due to natural flow restrictions and friction against the riverbed and riverbanks, the most optimal location for energy extraction in a river needs to be studied thoroughly. If the turbine is not placed in the most optimal location, it will not capitalize on the most energy-rich flow in the river. Another consideration is that the velocity and water depth in the river will change in response to changes in the flow condition.

The International Electrotechnical Commission (IEC) published standards for riverine hydrokinetic resource assessments, and it recommends using a 15-point flow duration curve (FDC), a type of probability distribution, to characterize the flow variation (IEC, 2019). However, past research has indicated that the distribution of flows may be suitably represented using a coarser FDC, comprised of fewer points, depending on the conditions of the river being studied (Kirby et al., 2022b). In the standards, the FDC should be based on 10 years of available data or modelled data with less than 10% calibration error. To develop the velocity duration curve (VDC) from the FDC, five velocity-discharge measurements at the location of interest can be used for projects with blockage ratios less than 5% (less than 5% of the channel cross section is blocked by the turbine swept area) and spacings between turbines of at least ten turbine diameters. For projects with

blockage ratios greater than 5%, and less than ten diameter spacings between turbines, or for which there are not five velocity-discharge measurements, a model can be used to simulate the relationship. To support model development, field measurements must be recorded during three different flow conditions in the study reach. For each surveyed flow condition, practitioners must record: (1) flow velocity measurements along two cross-sections to support model calibration, and (2) velocity measurements at two potential turbine deployment locations to support model validation. It is recommended that there should be less than 10% model error (IEC, 2019). Annual energy production (AEP) is calculated based on the VDC, the assumed number of hours per year the turbine will operate, and the turbine's velocity-power relationship. For collection of the field data, the IEC (2019) standards refer to the International Hydrographic Organization's Standards for Hydrographic Surveys (2020). So far, no studies have met these standards, likely because the IEC (2019) standards were produced in response to the inconsistencies in the published methods and results at that time.

The seasonal variation of flow is not often considered in existing hydrokinetic energy resource assessments. Table 3-1 illustrates 17 hydrokinetic energy assessments conducted in the past and whether seasonal flow variation was considered in the estimation of hydrokinetic energy.

Table 3-1: Consideration of seasonal flow variation in 17 hydrokinetic energy resource assessments completed between 2011 and 2020 (Adeogun et al., 2020; Ali et al., 2020; Arango, 2011; Cornett and Faure, 2015; Duvoy and Toniolo, 2012; Filizola et al., 2015; Holanda et al., 2017; Kalnacs et al., 2014; Kasman et al., 2019; Lata-García et al., 2018; Montoya Ramírez et al., 2016; Nhabetse et al., 2017; Nordino, 2016; Petrie et al., 2014; Punys et al., 2015; Santos et al., 2019; Saupi et al., 2018).

Consideration of seasonal flow variation	Number of studies
Not considered	7
Three conditions considered: maximum flow, average flow, and minimum flow	3
Regression relationship from historical data used to characterize the flow variation's impact on energy	5
Statistical representation from historical data used to characterize the flow variation's impact on energy	2

Petrie et al. (2014), Kalnacs et al. (2014), Filizola et al. (2015), and Montoya Ramírez et al. (2016) did not consider seasonal variation of flow in their assessments of hydrokinetic energy potential. Other studies such as Nordino et al. (2016) generated a VDC from 5 years of discharge data, Holanda et al. (2017) considered maximum, minimum, and mean

discharge conditions, and Kasman et al. (2019) used five years of discharge data to develop their simulation. Other studies, such as Pacot et al. (2019) performed a similar analysis, but in a trapezoidal flume, which does not account for the complex morphology and flow patterns that exist in a natural channel. Toniolo et al. (2010) studied a natural river reach with an acoustic Doppler current profiler (ADCP) to collect velocity data but only performed the analysis under one flow condition which does not consider the influence of flow variation on the optimal turbine location. Kirby et al. (2021) also studied a river reach with ADCP technology to analyze the best turbine location, but again the analysis was conducted for a single flow condition only. Holanda et al. (2017) also considered different flow conditions – an average flow, a minimum flow, and a maximum flow – but the influence of those three flow conditions on the optimal turbine location was not explicitly studied. Ultimately, there is a research gap where no studies have explored the possibility that the optimal turbine placement within a river reach may change with flow condition. For example, perhaps the best area to deploy a turbine in low flow is less efficient in high flow conditions where an alternative, better, location may exist. Additionally, the IEC (2019) standards for riverine hydrokinetic assessments has not been tested yet.

The objective of this study was to investigate the impact of flow condition and flow variation on hydrokinetic energy resources in rivers, as well as implications for optimal turbine placement. Furthermore, the study investigated the benefit of analyzing spatial variation of the depth-averaged velocity flow field, in contrast to previous, less spatially intense methods that consider only reach-averaged estimates. In order to perform this analysis, the following steps were undertaken: (1) data collection from the river reach in the field; (2) generation, calibration, and validation of a hydrodynamic model using the field data collected from step 1; (3) generation of velocity flow field data from the calibrated hydrodynamic model created in step 2 at various flow conditions; (4) calculation of the expected hydrokinetic energy from the simulated velocity flow fields in step 3; and (5) analysis of the data generated from the model in step 3 to understand if and how optimal turbine location changes with seasonal flow variation.

3.2 Study Location

The reach chosen to investigate the relationship between discharge and riverine hydrokinetic energy is a lower portion of the Rivière Rouge, Québec, Canada just upstream of the confluence with the Ottawa River. The reach is located approximately at 45.6449° latitude and -74.6906° longitude and approximately 150 km east of Ottawa, Ontario, Canada.

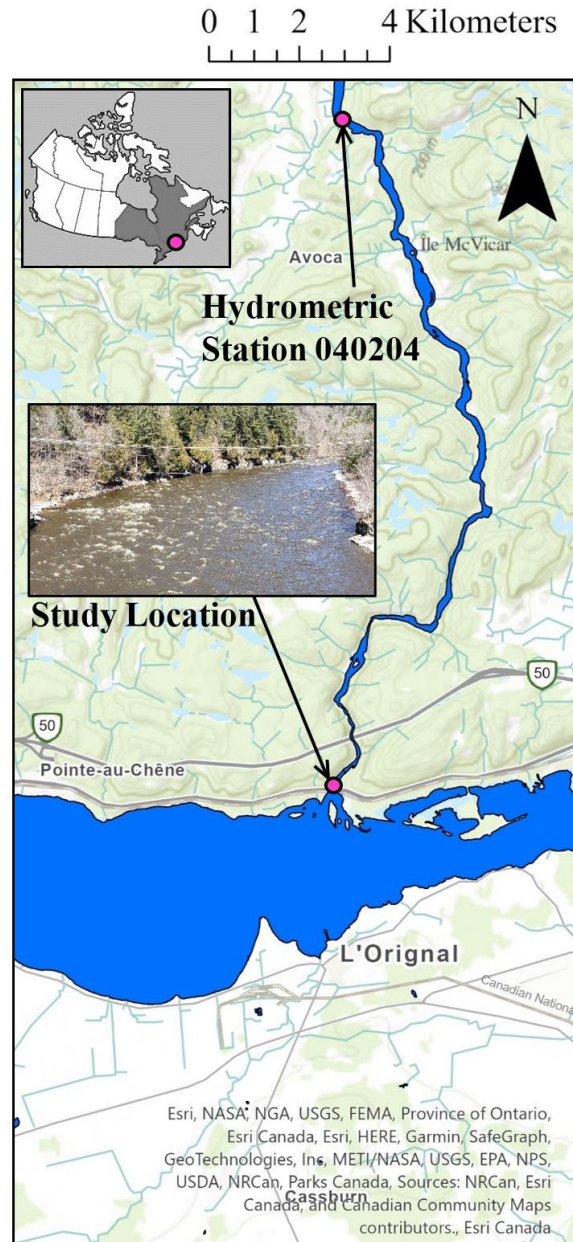


Figure 3-1: Location of the study area on the Rivière Rouge, just upstream of the confluence with the Ottawa River, and the hydrometric station from which flow data was collected. Water polygons are from the Canada National Hydro Network (Natural Resources Canada; Government of Canada, 2017).

The river runs in a general north-to-south direction and discharges into the Ottawa River. The river reach was chosen for this study because it always contains open water in winter months (i.e., December, January, and February) as determined from Sentinel-2 and Landsat satellite imagery. Open water in the winter is a good indication of desirable high energy flow conditions (d'Auteuil et al., 2019), such as high velocity conditions downstream of rapids. Lack of river ice also simplifies turbine operation as well as

maintenance of turbine power cables. Site accessibility was also considered, as river reaches with high energy flow are often inaccessible by boat. In this case, the reach was accessible from the marina at L'Original, Ontario, which is located directly on the other side of the Ottawa River. The reach is characterized by a boulder, gravel, and sand riverbed. A bedrock cliff forms the west bank of the reach and the east bank is comprised of boulders, gravel, and sand. The study reach is 280 m long and an average of 60 m wide. The average flow for the river is approximately 70 m³/s. River flows in the study reach are influenced by natural, seasonal variation (i.e., spring freshet) as well as dam operations associated with the Bells Falls dam, located 17 km upstream of the study reach. Hydrometric gauge station 040204 (federal station 02L029) is operated at McNeil Falls 13km upstream of the study reach (latitude 45.73639°, longitude -74.68972°) by the Ministry of the Environment and the Fight against Climate Change, Québec. This gauge station provided 57 years of daily discharge data (from 1964 to current), from which the flow probability distribution in Figure 3-2 was produced.

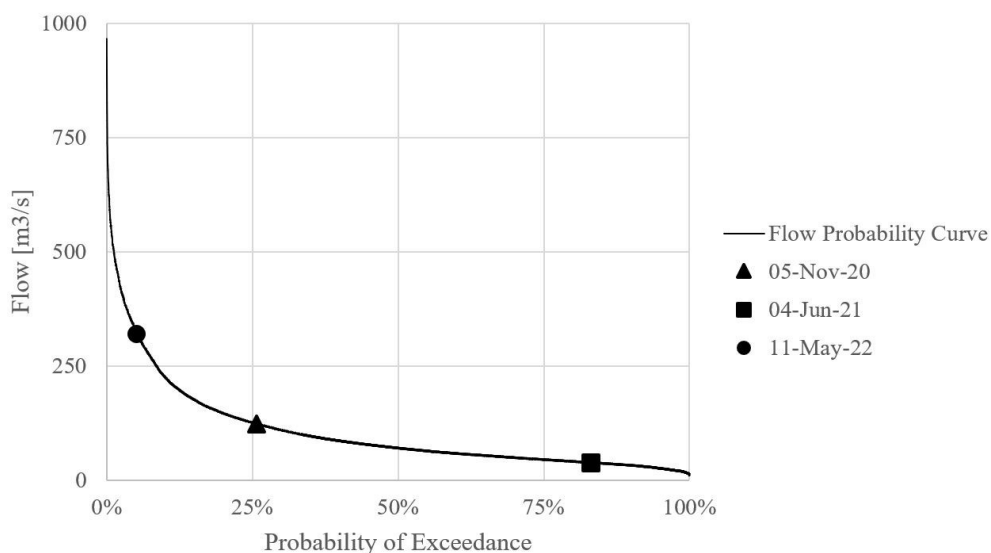


Figure 3-2: Flow probability distribution for the study area. The three flow conditions that field surveys were conducted are illustrated as points on the figure.

The figure characterizes the types of flows that can occur on the Rivière Rouge and how often those flows can occur. The three points on the graph, 05-Nov-2020, 04-Jun-2021, and 11-May-2022, show the flow conditions on the days that surveys were conducted. Some discrepancy is expected between flows recorded at the gauge station and flows at the study reach owing to the distance between the two locations; however, the gauge station is relatively close in proximity. For comparison, the Rivière Rouge watershed drainage area that drains into the gauge station location is 5460 km², and the drainage area contributing to the survey location is 5540 km² (Organisme de bassins versants des rivières Rouge, Petite Nation et Saumon, n.d.).

The Ottawa River, which the Rivière Rouge discharges into, was observed to influence the downstream water elevation of the study area. In conditions where the Ottawa River water elevation was high, the Ottawa River filled the south end of the study area. Figure 3-3 illustrates the average monthly flow of the Rivière Rouge and the expected downstream water elevation of the study area (i.e., the Ottawa River's monthly average water surface elevation).

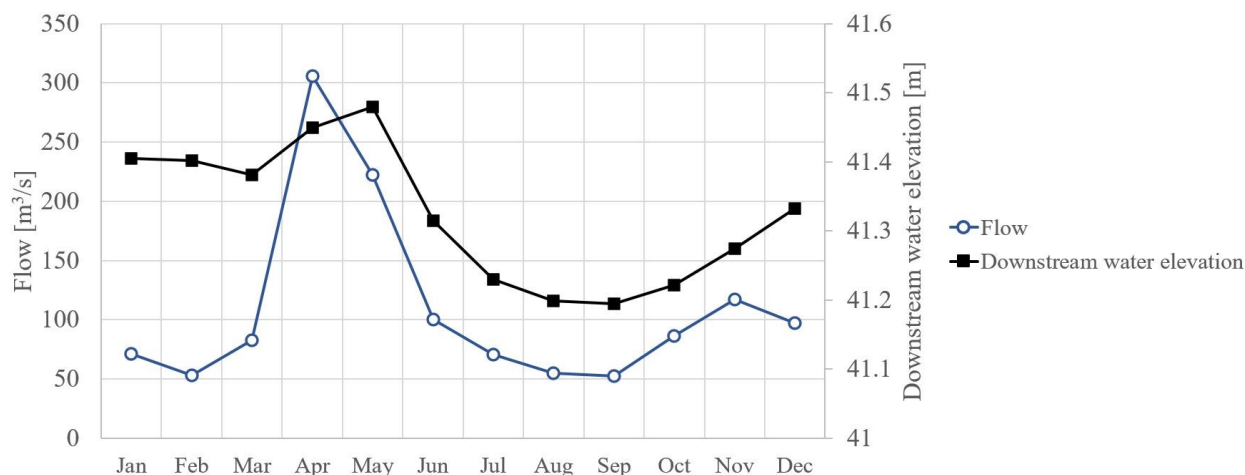


Figure 3-3: The average monthly flow and the expected monthly average downstream water elevation of the study area.

The downstream water elevation data for the Ottawa River was obtained from the Ottawa River Regulation Planning Board website (“Ottawa River Regulation Planning Board,” n.d.). The Grenville station is 8km downstream of the study site, and the Thurso station is 46km upstream of the study site. Monthly average water surface elevations at both stations were calculated using the last 20 years of data, and the monthly averages were linearly interpolated using the distance to the study site to determine each monthly downstream boundary condition at the study site.

3.3 Methods

3.3.1 Field Measurements

To model the study reach in multiple flow conditions, riverbed elevation data were required to determine the bathymetry of the reach, and velocity and water surface elevation measurements were required to calibrate and validate the model results. Data were collected using an ADCP equipped with a global positioning system (GPS); positional accuracy was enhanced using either real-time kinematic (RTK) positional correction or WAAS. Three surveys were conducted, one on November 5th, 2020, another on June 4th, 2021, and the last on May 11th, 2022. As illustrated in Figure 3-2, the November 5th flow was a “mid-high flow” condition, the June 4th flow was a “low flow” condition, and the May 11th flow was a “high flow” condition. The ADCP was towed to the

side of a 25 HP motor boat (November 5th), in a floating boat behind a canoe (June 4th), and in a remote-control boat (May 11th). The June 4th survey was conducted in a canoe because the water depth was too low for a motor boat to be used, and the May 11th survey was done using a remote-control boat because the high flow conditions were too dangerous for the research team to be in the water. The data in the November 5th survey were position corrected with RTK-DGPS which allowed for positional accuracy of approximately 1 cm. The June 4th and May 11th surveys were conducted without position correction from RTK-DGPS, resulting in positional accuracy of 1 m. The data were collected in a zig-zag pattern from bank to bank with approximately 1/5 of the river width (12 m) as the distance between zig-zag transects (shown in Figure 3-4), as this has been recommended to be best practice (Rennie and Church, 2010). The sampling frequency was 1 Hz. Riverbed elevation data from the November 5th survey were used to construct the hydrodynamic model bathymetry; riverbed elevation measurements were interpolated onto an unstructured computational mesh using Blue Kenue® software (Canadian Hydraulics Centre, 2011), as illustrated in Figure 3-5a. The model was calibrated using velocity data and water surface elevation recorded during the November 5th survey and the model was validated using velocity data collected during the June 4th and May 11th surveys.

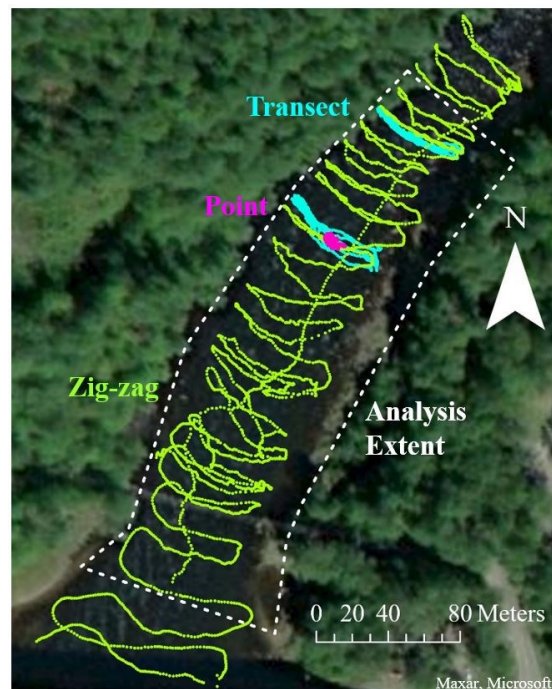


Figure 3-4: The data collection extent of the field measurement survey conducted on November 5, 2020 on the Rivière Rouge.

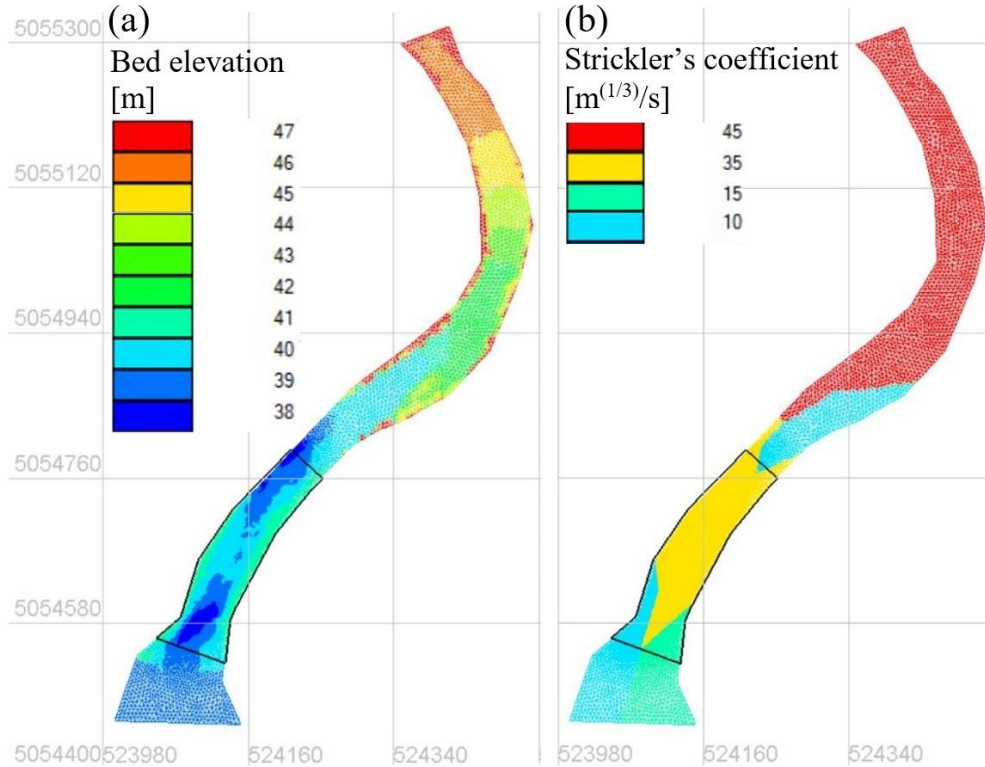


Figure 3-5: (a) Hydrodynamic model domain of the study site and upstream model extension and (b) varied roughness values (Strickler's coefficient). The black outline is the field data collection area (the zig-zag survey extent), and coordinates are WGS 1984 UTM Zone 18N.

For all three surveys, in the two areas that were determined to be highest velocity from the zig-zag survey, two transect surveys were conducted (shown in Figure 3-4 in blue) with six cross sectional measurement tracks taken at each location (back and forth three times). This was to increase spatial intensity at the locations of interest. Further, a point survey was conducted at the location that was estimated to be highest velocity from the two transect surveys (Figure 3-4 in pink). Channel bathymetry was extrapolated eastward of the November 5th survey extent, via visual interpretation, to facilitate simulation of flow conditions greater than those observed on November 5th.

3.3.2 Hydrodynamic Model

For this study, two-dimensional hydrodynamic modelling was conducted using TELEMAC-2D version 7.2. TELEMAC-2D is an open-source, numerical hydrodynamic model that uses the shallow water equations to solve the fluid flow throughout the computational domain (Ata, 2017). In a comparison of six numerical modelling software programs, and their ability to simulate the velocity flow field, Rousseau et al. (Rousseau et al., 2016) found that TELEMAC-2D generally outperformed other modelling software. Computations were performed on an unstructured computational mesh that conformed to the shape of the river boundaries. To generate the model domain, Blue Kenue[®] software

(Canadian Hydraulics Centre, 2011) was used to create the computational mesh illustrated in Figure 3-5a. The areas of interest (i.e., locations where high velocity flows are likely) had a mesh resolution of 1 m and the banks and areas of lesser interest had a mesh resolution of 5 m. The study reach (indicated by the white outline in Figure 3-4) was in the middle of a bend, as seen in satellite imagery. Likewise, flows along the west (outer) bank were generally deeper and faster than flows along the east (inner) bank, particularly near the northern (upstream) extent of the study reach. An upstream extension was added to the model domain to provide additional room for flow to develop prior to entering the area of interest. This extension had a mesh resolution of 5 m throughout. An initial estimation of the upstream extension's bed elevation was completed using the CanElevation high resolution digital surface model (Natural Resources Canada, n.d.). The bathymetry and roughness of the extension were adjusted to best replicate the flow distribution observed in the study reach. Total roughness (grain roughness and form roughness) was represented using the Strickler coefficient, a measure of the riverbed irregularity caused by the size and shape of riverbed material, vegetation, meandering, and obstructions. In TELEMAC-2D, the Strickler coefficient represents the inverse of Manning's roughness. A flow condition was specified for the upstream boundary and a water level condition was specified for the downstream boundary.

Field observations from the November 4th, 2020 survey were used to support model calibration. An upstream flow condition of 135 m³/s and a downstream water elevation condition of 42.0 m was specified based on field observations from November 4th, 2020. Calibration was done by adjusting the roughness parameter (i.e., Strickler coefficient) and the velocity diffusivity to minimize the root mean squared error (RMSE) between modelled and measured depth-averaged velocities, according to the equation below:

$$[3-2] \text{ RMSE} = \sqrt{\frac{\sum_{i=1}^N (v_i - \hat{v}_i)^2}{N}}$$

where N is the number of field data points, v_i is the observed depth-averaged velocity, and $\hat{v}_i$ is the modelled depth-averaged velocity. Additional metrics were used to quantify model skill including mean error (ME), standard deviation of error (SDE), mean absolute error (MAE), and mean absolute percentage error (MAPE), which were calculated using the equations below:

$$[3-3] \text{ ME} = \frac{\sum_{i=1}^N (v_i - \hat{v}_i)}{N}$$

$$[3-4] \text{ SDE} = \sqrt{\frac{\sum_{i=1}^N ((v_i - \hat{v}_i) - \text{ME})^2}{N-1}}$$

$$[3-5] \text{ MAE} = \frac{\sum_{i=1}^N |v_i - \hat{v}_i|}{N}$$

$$[3-6] \text{MAPE} = \frac{1}{N} \sum_{i=1}^N \frac{|v_i - \hat{v}_i|}{v_i}$$

It is possible to further calibrate the model velocity by the velocity diffusivity using 3-dimensional velocity data and the methods proposed by Parsapour-Moghaddam and Rennie (2018) and Williams et al. (2013). However, for the purposes of this study, further calibration of the model was not needed, as the resulting simulated velocity data compared fairly well with the collected field data in the areas of interest. The model was validated using the two additional surveys on June 4, 2021 (flow equal to 38 m³/s and downstream water elevation of 41.2 m) and May 11, 2022 (flow equal to 306 m³/s and downstream water elevation of 41.2 m). Similar to the calibration, the validation metrics were the RMSE, ME, SDE, MAE, and MAPE of depth-averaged velocity.

Additionally, the variance of flow velocity measured at a fixed point (see Figure 3-4), was calculated using the following equation:

$$[3-7] S^2 = \frac{\sum_{i=1}^N (v_{pi} - \bar{v}_{pi})^2}{N-1}$$

Where S^2 is the variance, v_{pi} are the observed depth-averaged velocities in the point surveys, and $\bar{v}_{pi}$ is the mean of all observed depth-averaged velocities in the point surveys. The numbers of depth-averaged velocity datapoints used in the variance calculation for the November 5, 2020, June 4, 2021, and May 11, 2022 surveys were 291, 352, and 13, respectively. The number of points in the May survey was comparatively low because a proper point survey could not be conducted in the high flow conditions.

3.3.3 Annual Hydrokinetic Energy Production and Optimal Turbine Location

With a calibrated and validated hydrodynamic model, river flows were simulated for a broad range of expected flow conditions (i.e., flow conditions other than those for which the data were taken). Simulated flow results were analyzed to understand the distribution of flow velocities (and energy resources) and estimate annual energy production (AEP).

The AEP is commonly calculated using the following equation and the study area's power duration curve (PDC)

$$[3-8] \text{AEP} = N_h \sum_{i=1}^{N_B} P_i B_i$$

where N_h is the number of hours of turbine operation in a year, N_B is the number of points on the PDC, P_i is the theoretical power present at the point on the PDC, and B_i is the width on the PDC that the point represents as a decimal probability. According to the IEC (2019) standards, the PDC should be derived from a 15-point FDC, where 15 flow conditions are simulated using a calibrated hydrodynamic model, and simulated velocities are translated to power using Equation 3-8. However, this particular study area on the Rivière Rouge did not permit this method of calculating the AEP, and an alternative

method of locating the optimal turbine location during different flow conditions was employed. Using a FDC to calculate the AEP assumes that a single velocity field exists for a given flow (or discharge) on the FDC. This is not the case for the Rivière Rouge, as a single upstream flow boundary condition did not correspond to a single downstream water surface elevation boundary condition, as illustrated in Figure 3-3. For example, the months of August and September exhibited similar average monthly flow, but the average monthly downstream water elevation is different. As such, a range of velocity fields are possible for a given flow, depending on downstream conditions which are dictated, in part, by flow conditions on the Ottawa River. Instead of utilizing a FDC, the monthly average conditions in Figure 3-3 were used to generate twelve velocity flow fields, corresponding to each month. After each velocity flow field was modelled, the northmost and southmost ten percent of the zig-zag survey extent were excluded from the analysis, as shown in Figure 3-4, to avoid errors associated with boundary effects. Using Equation 3-1, the power was calculated for the average reach velocity, top ten percent velocity, top five percent velocity, and top one percent velocity, assuming a turbine swept area of 1 m^2 . Each of the resulting twelve power values were converted to energy, assuming the turbine used would be operating at all times. Energy estimates were summed to calculate the AEP. Efficiency losses and optimal turbine operation such as cavitation prevention were not considered in the theoretical estimation.

To analyze the optimal turbine location under various flow conditions, the locations of the top ten percent, top five percent, and top one percent of velocity values were detected for each of the twelve velocity flow fields corresponding to the average monthly conditions. As shown in Equation 3-1, the locations best suited for turbine placement are those of high velocity. Only velocity was considered in this study to select optimal turbine locations, and other factors such as water depth, additional water uses, and proximity to electricity users or transmission lines were not considered. Each velocity flow field from the TELEMAC-2D model consisted of 10550 nodes for which a depth-averaged velocity value was estimated. As such, the 1055 nodes with the highest velocity were used to locate the top ten percent velocity locations, the 528 nodes with the highest velocity were used to locate the top five percent velocity locations, and the 106 nodes with the highest velocity were used to locate the top one percent velocity locations. Visualizing these three criteria using ArcGIS Pro 2.9.0 allowed for analysis of if and how the optimal turbine location changes with flow condition.

3.4 Results and Findings

3.4.1 Calibrated and Validated Model

The hydrodynamic model was calibrated primarily by adjusting the roughness parameter, separated into three general areas: the upstream extension, the main analysis area, and the downstream area. The final roughness used in the calibrated model is

illustrated in Figure 3-5b. The roughness parameter was adjusted until the RMSE was minimized. The upstream extension roughness parameter was adjusted to a Strickler coefficient of $45 \text{ m}^{1/3}/\text{s}$ (Manning's roughness of $0.022 \text{ s}/\text{m}^{1/3}$) to increase velocity at the north model domain to match the observed values. A small section of the east upstream extension was increased to a Strickler coefficient of $10 \text{ m}^{1/3}/\text{s}$ (Manning's roughness of $0.1 \text{ s}/\text{m}^{1/3}$) to force the flow towards the west bank of the reach, as this is what was observed in the field. The main analysis area roughness parameter was adjusted to a Strickler coefficient of $35 \text{ m}^{1/3}/\text{s}$ (Manning's roughness of $0.029 \text{ s}/\text{m}^{1/3}$). A Strickler coefficient of $10 \text{ m}^{1/3}/\text{s}$ and $15 \text{ m}^{1/3}/\text{s}$ (Manning's roughness of $0.1 \text{ s}/\text{m}^{1/3}$ and $0.067 \text{ s}/\text{m}^{1/3}$) was specified for the western and eastern portion of the channel, respectively, in the downstream area of the model domain. The riverbed was comprised of gravel, rock, and boulders, and the reach is directly downstream of rapids. For natural channels, Manning's roughness values generally range from $0.030 \text{ s}/\text{m}^{1/3}$ (for clean, straight channels) to $0.080 \text{ s}/\text{m}^{1/3}$ (for channels with dense vegetation) (Arcement Jr. and Schneider, 1989). The resulting velocity flow field from the calibrated model is illustrated in Figure 3-6.

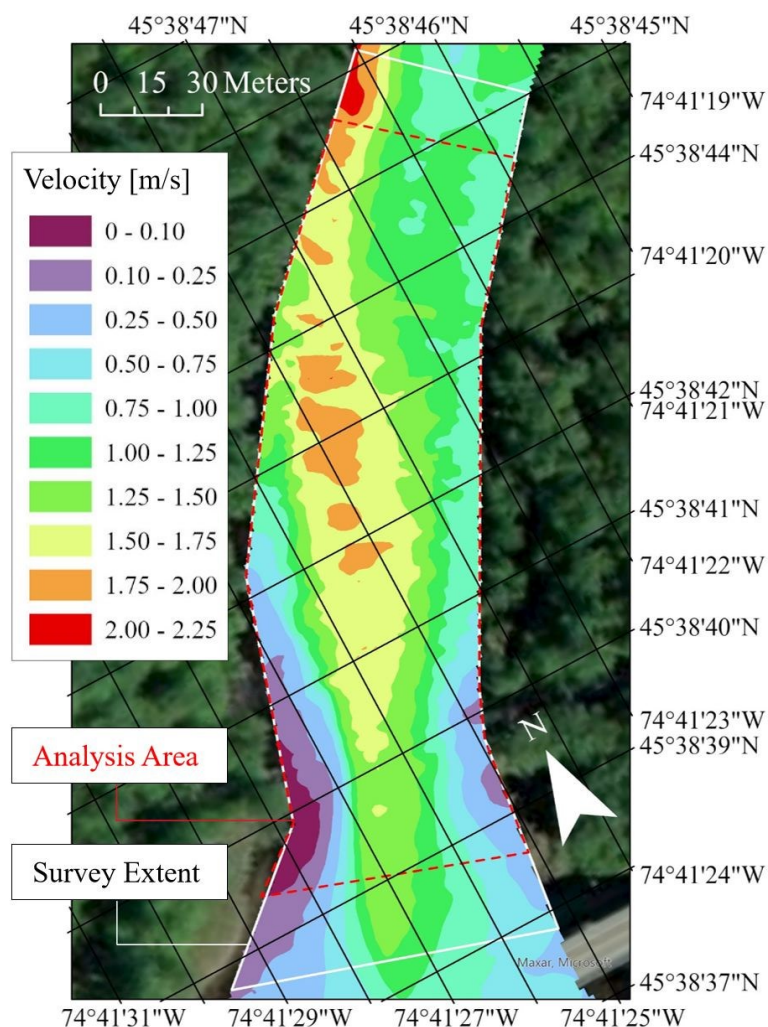


Figure 3-6: The calibrated model's depth-averaged velocity flow field results, clipped to the analysis area, for the November 5, 2020 flow condition.

The range of velocity magnitudes within the reach and the distribution of velocities within the analysis area were visually similar to that of the measured values. Error statistics from the calibration and validation of the hydrodynamic model are presented in Table 3-2. The model showed good agreement with measured values. Table 3-2 also shows the variance of the field data from the point surveys.

Table 3-2: Velocity error statistics of hydrodynamic model. The upper values are for the entire analysis area (Figure 3-6) and the lower values in brackets include only the highest velocity locations (Figure 3-9).

Survey Date		Flow [m ³ /s]	Variance [m/s]	RMSE [m/s]	ME [m/s]	SDE [m/s]	MAE [m/s]	MAPE [%]
05-Nov-2020	Calibration	135	0.07	0.29 (0.33)	0.09 (0.15)	0.28 (0.29)	0.23 (0.26)	18.9 (14.8)
04-Jun-2021	Validation	38	0.01	0.18 (0.19)	0.08 (0.10)	0.16 (0.16)	0.14 (0.15)	53.6 (22.9)
11-May-2022	Validation	306	0.20	0.51 (0.68)	-0.10 (-0.05)	0.15 (0.68)	0.39 (0.53)	20.2 (19.4)

3.4.2 Hydrokinetic Energy Analysis

Twelve flow conditions were simulated to represent average monthly conditions of the study site corresponding to Figure 3-3. From the generated velocity flow fields, the reach-averaged velocity, the top ten percent velocity, the top five percent velocity, and the top one percent velocity were extracted to calculate the potential theoretical hydrokinetic energy using Equation 3-1. The results of the reach-averaged, top five percent, and top one percent velocities are illustrated in Figure 3-7.

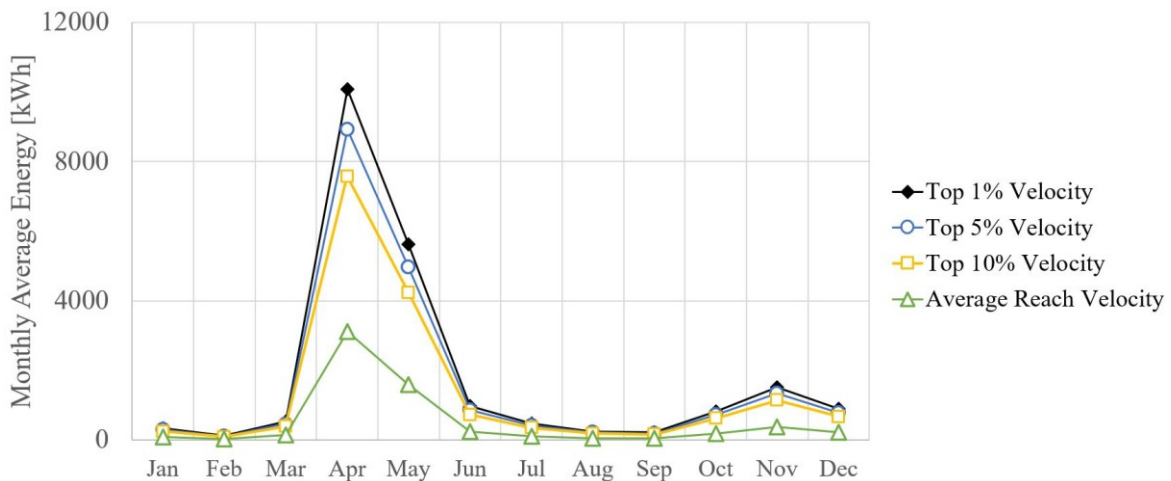


Figure 3-7: Theoretical hydrokinetic energy at the Rivière Rouge study site.

Figure 3-7 demonstrates the theoretical hydrokinetic energy extracted by a single turbine with a swept area of 1 m^2 , and the estimation does not include efficiency losses or any other practical consideration. A large disparity exists in the expected energy on a monthly basis. By far, the highest contributing months are April and May, corresponding with the spring freshet. Conversely, the results indicate low theoretical hydrokinetic energy availability during the summer and winter months when low flows are expected. Of the total annual available power, 72% is attributed to April and May. By summing the monthly average energy estimates, the AEP can be calculated. When considering the reach-averaged velocity, the AEP for a single turbine with a swept area of 1 m^2 is 6.2 MWh. When considering the top five percent velocity value, the AEP is 19.3 MWh (211% higher than the reach-averaged velocity), and when considering the top one percent velocity value, the AEP is 21.8 MWh (251% higher than the reach-average velocity and 13% higher than the top five percent velocity). These differences illustrate the potential benefits of conducting detailed assessments that account for spatial flow variability, as opposed to simplified assessments that rely on generalized, reach-representative values. By understanding the spatial variability of flow velocity and energy resources, developers can better strategize turbine placement within the river to optimize energy extraction. Essentially, if a similar methodology is employed to assess the hydrokinetic resource in other rivers, developers can capitalize on the most energy-rich locations within the river by strategically deciding to deploy turbines in the identified optimal locations. In addition to spatial variability, temporal variation in flow velocity (i.e., magnitude and distribution of flow velocity in the reach during different, characteristic seasonal flows) may also influence turbine placement strategy and optimization. Thus, the optimal turbine locations for every month were compared and these results are presented in Section 3.5.2.

The relationship between flow and hydrokinetic power at the site is illustrated in Figure 3-8.

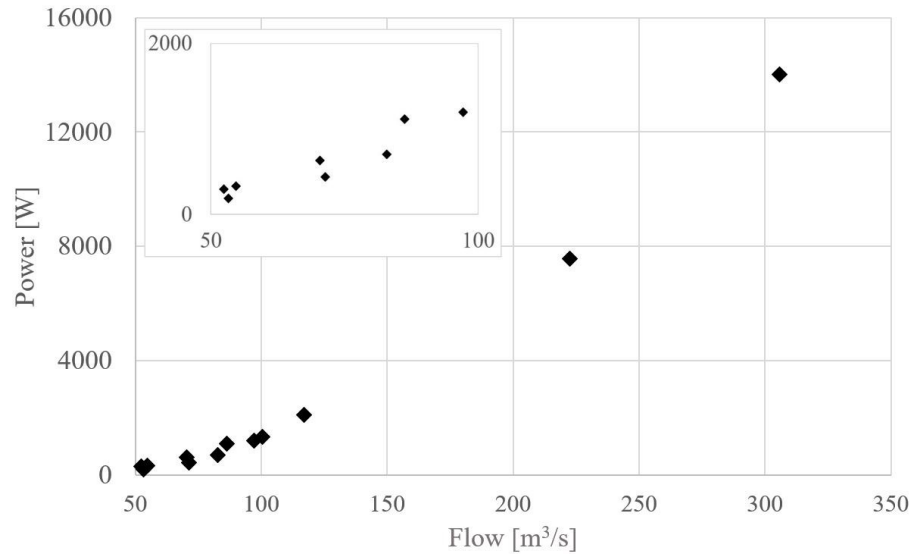


Figure 3-8: The relationship between flow and available hydrokinetic power at the study site at the top one percent velocity locations.

The expected power increases with flow in an approximate second-degree polynomial relationship at the top one percent velocity locations. Some scatter exists at the low flow end, which is visually magnified in the top left corner of the figure. This scatter can be explained by the different downstream water elevations used in the model, as explained in Section 3.3.3. For example, the three lowest flow points (left-most points) are in the range of 53.2 to 54.7 m³/s. The two points within the cluster with the higher power values were the flows corresponding to September and August with downstream water elevations of 41.2m. The single point within the cluster with the lower power value was the February flow with a downstream water elevation of 41.4m. This result is indicative that the model is performing properly with lower downstream water elevation corresponding to higher velocity in the reach.

3.4.3 The Optimal Turbine Location

For each of the twelve velocity flow fields, the optimal turbine locations were identified by selecting the locations with the top ten percent, top five percent, and top one percent of velocities within the reach at the particular flow condition, based solely on the notion that higher velocities imply greater suitability for turbine placement. To simplify the analysis, factors such as depth, substrate type, ease of installation or maintenance were not considered in this analysis. It was found that the months with mid to low flows had similar optimal turbine locations. Months that coincided with high flow (April and May) had similar optimal turbine locations to one another. Figure 3-9 illustrates each node of optimal turbine placement in the reach for April and December. There are four general areas of optimal turbine placement, as illustrated on the figure: (1) 90m, (2) 120m, (3) 180m and (4) 220m downstream from the upstream boundary.

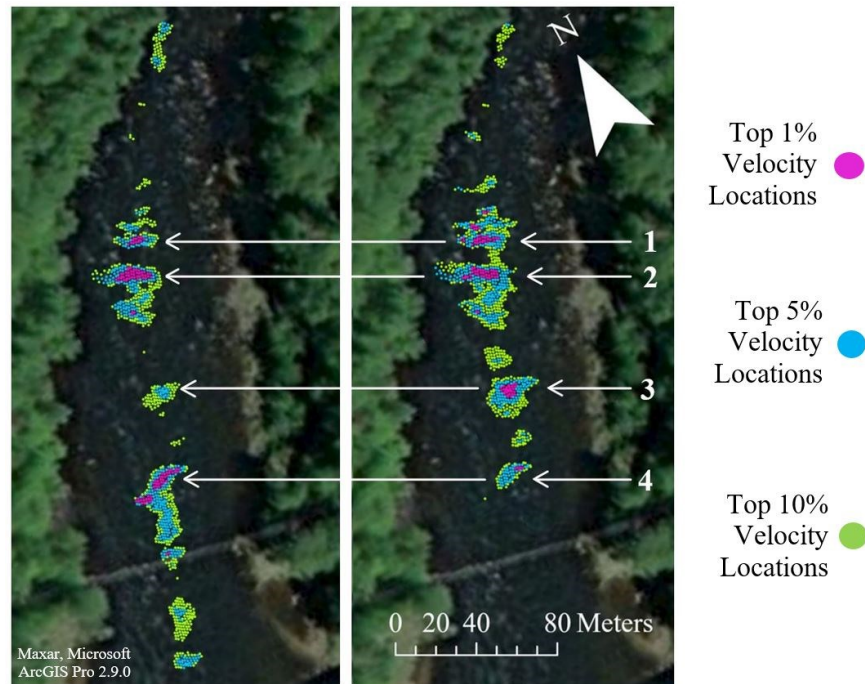


Figure 3-9: (Left) The optimal turbine locations in April and (right) the optimal turbine locations in December.

3.5 Discussion

3.5.1 Hydrokinetic Power Feasibility at the Study Site

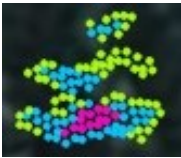
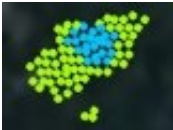
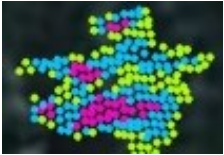
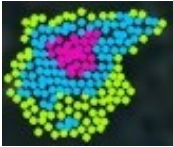
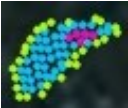
It is generally accepted that a river reach can be feasible for hydrokinetic energy extraction if the velocity is greater than 1.5 m/s; this river reach meets that criterion, but it is much more useful to compare the expected AEP to previous literature to determine if this reach is expected to be feasible. For example, a river reach with a velocity range of 0.88 to 1.88 m/s was studied by Nag and Sarkar (2021), which is a similar condition to this reach of the Rivière Rouge. The turbine array studied consisted of 24 turbines. The array was expected to produce 524 kWh per day, accounting for turbine efficiency losses. This equates to 8.0 MWh per year for a single turbine with an unknown swept area. This value is similar to our estimates for theoretical power in the Rivière Rouge (6.2 MWh per year for a single turbine with 1m² swept area using reach-averaged velocity, and 21.8 MWh per year using velocity at the optimal turbine location). Holanda et al. (2017) conducted a similar study with a ten turbine array which was expected to produce 2.04 GWh per year. The turbines considered had a swept area of 10 m², and the array was designed to be situated directly downstream of a hydropower dam. Adjusting the swept area and number of turbines, Holanda et al. (2017) expected 20.4 MWh per year, per 1 m² swept area turbine to be produced. It is common that multiple turbines would be deployed in an array, and consideration of an array rather than a single turbine could

increase the feasibility of this reach for energy extraction. In the province of Ontario, Canada (the province adjacent to Québec) the average household used 708 kWh of electricity per month in 2016 (Financial Accountability Office of Ontario, 2019). If ten turbines, each with a 1 m² swept area, were deployed in this reach in the areas of maximum power availability, theoretically, 25 households could be powered by the ten turbine array. This estimation does not include efficiency losses, flow interaction between turbines, turbine cut-out and cut-in speeds, and other practical energy extraction considerations. Ultimately, findings indicate that this reach of the Rivière Rouge could be a feasible candidate for energy extraction based on availability of theoretical energy resources. Following methodology from Nag and Sarkar (2021) and/or Fouz et al. (2022), a more detailed assessment of energy resources, accounting for efficiency losses and total cost of energy, could be conducted to better define technical and practical feasibility.

3.5.2 Flow Condition and the Optimal Turbine Placement

It is evident from Figure 3-9 that the optimal turbine location within this reach of the Rivière Rouge changes slightly with seasonal variation. The four locations of highest velocity (indicated in Figure 3-9) are shown in detail in Table 3-3, to better illustrate differences between high and low flow conditions.

Table 3-3: Comparison of the optimal turbine locations at different flow conditions.

Flow Condition	Location 1	Location 2	Location 3	Location 4
High Flow				
	14 49 58	46 124 113	0 23 59	45 86 53
Mid and Low Flow				
	35 105 75	38 171 160	27 86 78	6 40 26

The numbers below the illustrations in Table 3-3 correspond to the number of nodes with (left to right) the top one percent velocity, the top five percent velocity, and the top ten percent velocity in the reach. The most optimal location within the reach (with the most

top one percent velocity nodes in pink) is location two, which is the same in both flow conditions. However, the second most optimal location is different between flow conditions: location one is second most optimal in mid to low flow scenarios and location four is second most optimal in high flow scenarios. Additionally, location three appears to be quite promising for energy extraction in mid to low flow conditions but is less attractive in high flow conditions. This finding is important, as it can greatly influence engineering design decisions for hydrokinetic energy developers. The findings indicate that temporal (seasonal) variation in river flow can influence the spatial distribution of hydrokinetic energy resources and, consequently, optimal turbine location. The significance of this finding is that the optimal turbine location within the river reach can change depending on the seasonal hydraulic conditions in the river. As such, developers should consider employing similar robust resource assessments that consider both spatial and seasonal variation of flows. These considerations contribute to improved decision making on turbine placement and deployment strategies by informing developers of the most energy-rich locations within the reach. Additionally, the results of employing the proposed methodology to estimate the resource will inform the developer of how these locations are expected to be impacted by the river's seasonal conditions. Ensuring that turbines are placed in the most energy intense areas of the reach will ensure that the cost of energy (i.e., price of investment per unit energy produced) is minimized.

3.5.3 Previous and Current Method Limitations

The methods applied in this study have more thoroughly considered the impact of seasonal flow variation than methods applied in previous literature. It has been uncommon for the impact of seasonal flow variation to be considered when estimating riverine hydrokinetic energy. Considering seasonal flow variation and modelling how that flow variation impacts the velocity flow field in the reach has a great impact on the final estimated AEP. Natural channels can exhibit complex geomorphology, and the resulting variation of channel shape across a reach can cause the velocity to vary substantially from one area to another, compared to a channel with a uniform cross-sectional shape and area. The bathymetry in non-uniform, natural channels can result in complex flow structures, such as turbulence, secondary flow, and vortical structures (Knighton, 1984). This is why a zig-zag survey with transect spacing of less than or equal to $1/5$ the channel width is ideal for channels with complex geomorphology. A less spatially intense data collection technique cannot properly capture the bathymetry of the study area; thus, the resulting simulated velocity flow field will be comparatively less accurate. This study is the first of its kind to utilize a zig-zag survey technique in river hydrokinetic energy resource estimation. This more spatially intense method of gathering field data also allows for more accurate model calibration and validation, as the entire velocity flow field is represented. The roughness parameter (i.e., the Strickler coefficient used in this study) can be adjusted spatially throughout the computational domain to more closely match the simulated velocity flow field to the measured velocity flow field. Conversely, other common field data

collection methods (such as point or cross-sectional surveys), utilized in previous riverine hydrokinetic energy estimation studies, that provide information only at discrete locations in the study reach may not be fine enough to facilitate such an approach to calibration and validation of the model. Calibration and validation of the reach using spatially intense data also provides a better understanding of the errors and shortcomings associated with the model results. Utilization of a zig-zag survey approach supported spatially dense field observations of the flow field which allowed for more precise calibration of the model to be performed and improved the accuracy of the simulated velocity flow field. Ultimately, the increased accuracy of the simulated flow field supported examination of the optimal turbine locations within the study reach. The seasonal flow variation was observed to impact the optimal turbine location. As shown in Figure 3-9 and Table 3-3, the most optimal turbine placement within the reach does not change, but the next three most optimal turbine locations can change between high flow and mid to low flow conditions. This consideration is important as it is common to consider turbine array deployment which would utilize multiple locations within the river reach. This type of analysis would not be possible without either a spatially intense survey or consideration of multiple flow conditions, both of which have not been used in previous study methodologies.

The IEC (2019) standard for riverine hydrokinetic assessments was useful for this analysis, as the methods for hydrodynamic modelling and field data collection were followed. As prescribed in the IEC (2019) standards, more than ten years of available gauge station data were used to characterize the seasonal hydrodynamic conditions, velocity-discharge relationships for the study location were simulated using a model, the model was developed using field measurements in three different flow conditions, and flow velocity measurements were used to calibrate and validate the model. However, methods to define a probabilistic representation of flow conditions (e.g., FDCs) were modified to address site-specific considerations. Because of the complex nature of this channel (i.e., the downstream water elevation being out-of-step with the FDC, as illustrated in Section 3), the AEP had to be calculated on a monthly basis using the corresponding monthly-based boundary conditions for the model rather than a FDC as suggested by IEC. Use of a FDC instead of a monthly average-based approach may not have yielded much different results, as the differing downstream boundary conditions only occurred in low to mid flow months, with the high flow months contributing to 72% of the total AEP. Furthermore, this method accepted 14.8%, 22.9%, and 19.4% error (MAPE) for the calibration and two validations, respectively, in the locations of highest velocity, whereas the IEC standards recommend less than 10% absolute error between predicted and measured current speed. Additionally, the IEC standards recommend validation with three additional measurements, compared to this study where the velocity was validated with two. Better adherence to the IEC standards would increase the accuracy of the assessment and the meaningfulness of the calculated AEP. However, it was unlikely that, if the model was calibrated further to 10% error, the results would have been noticeably

different. For locations that are expected to undergo development, the standard should be followed, and thus, the required electromagnetic equipment used to extract the potential power would be properly sized to the application. Additionally, the IEC standards state that turbine impacts on hydrodynamics must be considered only for large projects where a 5%, or greater, blockage ratio is expected. Although it was not required for this study's analysis, the impact of hydrokinetic turbines on the hydrodynamics, sediment transport, and ecology of the river environment should be thoroughly understood before development. The purpose of this type of analysis would be to avoid or reduce the impact of the turbine on the river's natural environment, such as altered nutrient transport, impact on fish, water level rise, or scour and depositional changes (Cada et al., 2007; Fantin-Cruz et al., 2020; Hill et al., 2016).

Limitations of this study should be considered by developers, as the particular characteristics for a river reach of interest may be different than in this case study. Only one river reach was considered in this study and caution should be taken not to extrapolate detailed results to other river reaches. For best practice, the entire methodology should be applied to other rivers to understand how the optimal turbine placement varies with flow. Explicitly, developers should collect field data that includes bathymetry (one survey), depth-averaged velocity flow field (three to four surveys), and water level elevation (three to four surveys and additional conditions on the FDC). Developers should choose a robust and accurate hydrodynamic model to simulate the river hydraulics based on the field data. Finally, the variation of hydrokinetic power distribution within the study area should be analyzed across the FDC. Rivers with complex morphology would have more spatially varying velocity, whereas straight river reaches with uniform morphology would be expected to have less spatially variable velocity. Depth requirements and constraints for turbine operation were not considered in this study, which is likely to make a significant difference in the optimal turbine locations; usually a minimum depth of 3 m is required to support operation of fully submerged turbines (Ranjitkar, 2020). For reference, depth in Location 2 (see Table 3-3) varied between approximately 1.6 m and 2.3 m during low and high flow conditions, respectively. The study did not consider other uses of the river that may interfere with the optimal turbine placement or turbine deployment feasibility in general, such as transportation or recreation. Additionally, it is not currently common practice in hydraulic modelling to use multiple models to verify results, but it is in other disciplines, such as climate modelling, ecological modelling, and hydrology (Rousseau et al., 2016). A sensitivity analysis by using multiple hydrodynamic models was not conducted for this study, but the robustness of these types of studies could be increased by verifying the model's findings with the results of a different model.

3.6 Conclusions

This study illustrates the importance of considering both flow condition and the depth-averaged velocity flow field when estimating hydrokinetic energy potential in a river reach. Through this analysis of hydrokinetic energy resources on the Rivière Rouge in multiple flow conditions, the impact of flow condition on hydrokinetic energy was shown. Although the most optimal turbine location in the study reach did not differ between low flow and high flow conditions, secondary locations did differ between flow conditions. Additionally, the velocity flow field should be considered in these types of studies by using a hydrodynamic model and spatially intense field data collection to calibrate and validate the model. It was shown that the average and maximum hydrokinetic energy values in this reach varied greatly, indicating that there is an optimal location for the turbine to be placed where the velocity is the greatest. This information cannot be captured by resource assessments that base analyses on reach-averaged values or less spatially intense methods.

This study reach may be promising for energy extraction with a theoretical maximum AEP of 21.8 MWh per year for a single, small turbine. Consideration of a turbine array, rather than a single turbine deployment, may make this reach more promising for feasible energy extraction. Presumably, because hydrokinetic energy assessments are relatively new, there is much future work to be done to increase the robustness of this work, especially considering the complex nature of the riverine environment. For example, in this case study, methods specified in the IEC (2019) standards had to be modified to account for back water effects from a confluence. The practicality of the IEC (2019) standards could be reviewed to understand if the methods are prohibitive to robust resource assessment in specific cases where backwater effects are influenced by a receiving waterbody. Furthermore, optimal turbine placement was impacted by seasonal flow variation. The methods and findings described in this study may provide guidance for enhanced resource assessment strategies that account for seasonal impacts on spatial distribution of energy resources. Existing resource assessment methods do not provide sufficient information to incorporate seasonal flow variation into turbine placement strategy and decision making. Understanding this information can help practitioners better strategize turbine deployment and minimize cost of energy production.

Chapter 4. Optimization of Surface Water Mapping Data

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Rennie, C.D., Poot, R., Ferguson, S., Cousineau, J., Nistor, I., 2024. Accuracy of Surface Water Maps Derived from Radar Satellite Imagery Compared to Multispectral Satellite Imagery. *Can. J. Remote Sens.* 50, 2433591.
<https://doi.org/10.1080/07038992.2024.2433591>

Abstract:

Optical and radar remote sensing are both used to map surface water features. Since use cases range considerably in the literature between applications, a direct comparison is warranted to assess how well each perform in a wide range of geographic settings using a range of classification methods. Thus, surface water maps generated from Sentinel-1 Synthetic Aperture Radar (S1SAR) and Sentinel-2 Multispectral Instrument (S2MSI) imagery were compared across four machine learning techniques and eight diverse image areas in Canada. Additionally, the polarizations and multispectral bands were varied to understand their effect. The results were validated using high resolution satellite imagery, and analysis of variance was calculated. S2MSI consistently produced higher accuracy surface water maps compared to S1SAR. Contrary to previous understanding, the cross-polarization did not produce significantly more accurate surface water maps than like-polarization, and the same was true for dual and single polarization. The introduction of an additional band of multispectral imagery improved accuracy significantly. In flooded conditions, dual polarization produced the best results, and for the detection of ice, cross-polarization produced the best results. These findings will increase the quality and efficient generation of surface water maps for water resource management, climate change impact studies, and other disciplines.

Keywords: Multispectral Sentinel-2 satellite imagery; synthetic aperture radar Sentinel-1 satellite imagery; classification detection of earth surface water; earth open water observation; comparison of remote sensing products and methods

4.1 Introduction

Remotely sensed radar and multispectral data has proven to be extremely useful in flood extent mapping for hazard assessment (Ghosh et al., 2022; Katiyar et al., 2021; Nemni et al., 2020; Tanim et al., 2022; Uddin et al., 2019), in creating time series of waterbody change for climate change analysis (Alcaras et al., 2022; Kseňak et al., 2022; Manaf et al., 2016), in rice paddy and other water-based agricultural land use mapping

(Boschetti et al., 2014), as well as many other surface water mapping applications (Setiawan et al., 2024). The Sentinel satellite constellation of the Copernicus program made available from the European Space Agency (ESA, 2024, 2023) has increased the coverage, resolution, and availability of both synthetic aperture radar (SAR) and multispectral satellite data. Both Sentinel missions provide global coverage, medium resolution (10 m to 60 m), and high-frequency pass products with differing levels of primary processing completed.

The difference in the signal reflectance between land and water in both SAR and multispectral imagery can be used to classify pixels into either land or water categories for the creation of surface water maps. Water generally absorbs the signal more readily than land. SAR products emit their own signal, are not affected by cloud cover, and can operate during night or day. Thus, if a specific date or condition is targeted for analysis, such as a flood event, SAR imagery is more likely to be viable to capture that event (Notti et al., 2018). SAR is also impacted by noise, namely signal or reflection disturbances caused by the atmosphere, such as thermal noise or land-based objects (e.g., surface water waves) (C. Li et al., 2023). Two polarizations are available for Sentinel-1 SAR (S1SAR) imagery: like-polarization, either VV or HH, and cross-polarization, either VH or HV (ESA, 2024). Additionally, the two polarizations can be combined for dual polarization, VV/VH or HH/HV and other combinations if VV, HH, HV, and VH are all available at the site of interest. On the other hand, multispectral satellite imagery, such as Sentinel-2 multispectral instrument (S2MSI), is a passive imager that relies on solar signal reflection, and thus the viability of the imagery is highly dependent on cloud cover and the day/night cycle (Chen et al., 2015; Huang et al., 2020). Multispectral imagery is less affected by noise than SAR. Additionally, the division of reflectance wavelengths into twelve bands of imagery allows for the optimization of reflectance values to improve classification between water and land pixels, as performed by Feyisa et al. (2014). The difference in water and land signal reflectance varies across the multiple bands of multispectral imagery. For example, the near infrared (NIR) and short-wave infrared (SWIR) bands have a greater difference in land and water reflectance compared to the red band and are often used for mapping surface water. Notably, few analyses have been conducted to directly compare the quality of surface water mapping results derived from multispectral-based imagery to the results derived from radar-based imagery. The few studies that have compared S1SAR to S2MSI for surface water mapping have been conducted to detect only a specific type of surface water in one location (e.g., pond detection (Haris et al., 2021), flood inundation extent (Ticehurst and Karim, 2023), reservoir detection (Souza et al., 2022)). Additionally, these studies have produced inconsistent results where S1SAR produced higher quality maps than S2MSI (Haris et al., 2021) but the opposite was found by other analyses (Souza et al., 2022; Ticehurst and Karim, 2023). Further study is required to identify and statistically quantify differences in surface water detection between S1SAR and S2MSI. If multispectral-based imagery can identify surface water

more accurately, it should be prioritized for surface water mapping, despite the greater viability of radar-based imagery.

Various optimizations exist to improve the classification of satellite imagery, which can be categorized into four groups: (1) pre-processing, (2) principal processing, (3) combination processing, and (4) post-processing. Pre-processing includes atmospheric and ground corrections, noise removal, filter applications, and many other imagery manipulation techniques intended to increase the accuracy of the surface water map before classification takes place. Principal processing is the main method applied to classify pixels (i.e., land and water) and can be a threshold, index, or machine learning approach, as well as many others. Combination processing refers to the combination of methods or inputs used to improve the classification accuracy. For example, the combination of S1SAR and S2MSI images (Manaf et al., 2016; Mansaray et al., 2020; Tang et al., 2022), spectral indices (e.g., normalized difference water index), and machine learning techniques (e.g., support vector machine) (Thati et al., 2021; Yilmaz et al., 2023) have been shown to improve the quality of surface water maps. Finally, post-processing includes any filters or introduction of other datasets (e.g., digital elevation models) used to improve the surface water map results. Because of the great number of pre-, principal, combination, and post-processing steps that can be used to improve the results of surface water maps for both S1SAR and S2MSI, only the processing steps that are necessary and similar between S1SAR and S2MSI will be performed herein to ensure like-to-like comparison for the S1SAR and S2MSI imagery. As such, unlike spectral index-based methods, machine learning methods can be applied to both multispectral and radar-based satellite imagery and will be used to compare the two, assuring comparable analyses.

In addition to the broader comparison of S1SAR to S2MSI imagery for surface water mapping, the specific polarizations of S1SAR and multispectral bands of S2MSI used for surface water classification have produced diverging results and research gaps are present. The use of like-polarization for reservoir detection (Souza et al., 2022) and flood area detection (Abbasi et al., 2023; Brisco et al., 2008; Twele et al., 2016) has been shown to outperform cross-polarization, and the use of cross-polarization has outperformed like-polarization for pond detection (Haris et al., 2021) and surface water in general, regardless of the water characteristics (Bangira et al., 2019). Between the two polarizations, cross-polarization is insensitive to waves on the water surface but is vulnerable to low back scatter values, resulting in high commission errors (C. Li et al., 2023). Conversely, like-polarization is sensitive to water surface roughness due to wind and can create omission error on the water surface due to noise (C. Li et al., 2023). Thus, it is generally recommended to utilize dual polarization for surface water mapping (Brisco et al., 2008; White et al., 2015), as the advantages of the cross- and like-polarizations are complementary and the combination of both is theorized to reduce classification errors

(C. Li et al., 2023). However, results comparing single polarization to dual polarization have also indicated that single polarization is sufficient for mapping open surface water (Irwin et al., 2018). Small performance improvements from single polarization to dual polarization have been illustrated for oil spill and ship classification in marine environments (Baek and Jung, 2021), but it is not clear if improvements of this degree are statistically significant to warrant the use of dual polarization in all surface water mapping applications. Similarly, it is not clear if the use of additional bands of multispectral imagery is required for improved classification of S2MSI imagery when applying machine learning classification methods. Generally for the classification of surface water, the NIR, green, and/or SWIR bands of multispectral imagery are used (McFeeters, 1996; Rogers and Kearney, 2004; Xu, 2006), and the addition of multiple bands of imagery for the classification via spectral indices has been shown to outperform single band thresholding (Boschetti et al., 2014; Jain et al., 2005; Sun et al., 2012). In particular, Feyisa et al. (2014) found that increasing the influence of the green band in the classification enhanced the separability between water and land pixels at shadowy locations. Although it has been shown that the green band can improve classification accuracy for index-based methods, it is not clear if the same holds true for machine learning-based classification techniques, another common method of surface water map generation.

Despite the significant advancements in remote sensing technology and the widespread use of SAR and multispectral imagery for surface water mapping, there remains a notable gap in the literature regarding the direct comparison of the quality and accuracy of surface water maps derived from S1SAR and S2MSI imagery across multiple locations and environmental conditions. While individual studies have evaluated the efficacy of each imagery source for specific applications, such as flood extent mapping or reservoir detection, few have undertaken a comprehensive comparative analysis to identify which source consistently produces more accurate results across diverse scenarios. In light of the research gaps identified, the objectives of this study were:

- **Evaluation of Polarization:** Investigate the impact of different polarizations in SAR imagery on the quality of surface water mapping. Specifically, the comparison will include like-polarization to cross-polarization and single polarization to dual polarization for S1SAR.
- **Assessment of Spectral Bands in Multispectral Imagery:** Evaluate the influence of different spectral bands in multispectral imagery on surface water mapping. The comparison will involve comparison of band 8 (NIR) to band 3 and band 8 (green and NIR) for S2MSI.
- **Comparison of SAR and Multispectral Imagery:** Compare the accuracy and reliability of surface water maps derived from S1SAR and S2MSI imagery across multiple locations and seasonal conditions.

Through these objectives, the study aims to address the existing research gap by providing empirical evidence and statistical quantification of the differences in surface water detection between SAR and multispectral imagery. By clarifying the strengths and weaknesses of each imagery source, our study aims to contribute to the advancement of remote sensing methodologies for water resource management and environmental monitoring.

4.2 Data and Study Locations

The S1SAR and S2MSI imagery was downloaded from the Copernicus browser (<https://browser.dataspace.copernicus.eu/>), and the high-resolution imagery was purchased through Apollo Mapping. High resolution imagery sources, resolutions, and imagery dates are listed in Table 4-1.

Table 4-1: Study images

Image Code	Location Description	High-res Image Source	High-res Image Date	S1SAR Image Date	S2MSI Image Date	River Flow Rate [m ³ /s]
Area 1A	Sylvia Grinnell River near Iqaluit, NU, Canada	WorldView-2 50cm	2018/07/21	2018/07/24	2018/07/21	178
Area 1B	-	PLÉIADES 1 50cm	2021/08/31	2021/08/25	2021/08/31	75
Area 2A	Red River near Morris, MB, Canada	PLÉIADES 1 50cm	2019/06/30	2019/06/28	2019/06/30	171
Area 2B	-	KOMPSAT-3 70cm	2017/04/06	2017/04/08	2017/04/06	1470
Area 3A	Fraser River in Fraser Canyon near Xaxli'p First Nation, BC, Canada	KOMPSAT-3 70cm	2020/09/08	2020/09/07	2020/09/07	2110
Area 3B	-	SPOT7 150cm	2019/07/21	2019/07/22	2019/07/20	3130
Area 4A	Rivière-Rouge & Ottawa River near L'Orignal, ON, Canada	TripleSat 80cm	2019/09/29	2019/09/23	2019/09/21	61 & 922
Area 4B	-	WorldView-1 50cm	2019/06/12	2019/06/07	2019/06/10	149 & 3585

The pixel resolution of S1SAR is 3.5m by 3.5m in the stripmap (SM) swath mode, 10m by 10m in the Interferometric Wide (IW) swath mode, and 40m by 40m in the Extra-Wide (EW) swath mode (Bourbigot et al., 2016). S1SAR has been operational from 2014 to

present with an exact 6-day repeat cycle between S1A and S1B. In December 2021, technical issues caused S1B to be defunct, reducing the repeat cycle to 12 days. S1C is set to be launched in 2024, which will increase the repeat cycle back to 6 days. Comparatively, S2MSI has a 10 day repeat cycle for each satellite (5-day repeat cycle for both satellites) and has been operational from 2015 to present. The pixel resolution of the most commonly used S2MSI bands for surface water mapping are 10m by 10m for the visible light and near-infrared bands (2, 3, 4, and 8) and 20m by 20m for the short-wave infrared bands (11 and 12).

The study encompasses diverse geographical regions, each providing unique environmental characteristics and challenges for surface water mapping:

- **Sylvia Grinnell River (Area 1):** Located in Nunavut, Canada, this area features a diverse landscape including an Arctic community, tundra, and a variety of differently shaped water bodies. September (Area 3A) and July (Area 2B) images capture different river flow conditions and seasonal tundra vegetation changes.
- **Red River (Area 2):** Situated in Manitoba, Canada, this area possesses built infrastructure, agricultural lands, and various types of water bodies (river, lagoons, oxbow lakes, etc.). Images taken during regular flow (Area 2A) and flood events (Area 2B) depict variations in water turbidity and ice presence.
- **Fraser River (Area 3):** Located in British Columbia, Canada, this region encompasses mountains, river canyons, barren land, and coniferous forests. July (Area 1A) and August (Area 1B) images capture fluctuating river flow conditions and seasonal mountain vegetation changes.
- **Rivière-Rouge (Area 4):** Spanning Ontario and Quebec, Canada, this location features sand bars, vegetated shorelines, deciduous vegetation, marshland, and urban areas. Images from low flow (Area 4A) and high flow (Area 4B) conditions illustrate shoreline inundation and river width changes.

Each location is analysed in two different seasonal conditions, providing comprehensive coverage of surface water dynamics and environmental variability. Table 4-1 provides a comprehensive overview of the imagery used for analysis, aiding in understanding the temporal and spatial context of the study areas. The source and resolution of each high-resolution image and the river flow rate on the image collection date (to represent the seasonality of the imagery) are also presented. The high-resolution images were used to validate the results of the surface water maps derived from S1SAR and S2MSI imagery. Although all study regions are located in Canada, the application of these findings to other regions is appropriate to some extent. The study locations are 3500 km apart in the longitudinal direction and 2100 km apart in the latitudinal direction. Additionally, the images contain a distinct variety of landcover classes and image characteristics (i.e., mountains, cropland, urban land, deciduous and coniferous vegetation, tundra vegetation, ice and snow, wide and deep rivers, narrow and shallow rivers, lagoons, oxbow lakes, vegetated shorelines, marshland, barren land, etc.). An

attempt was made to include as many landcover classes as possible when selecting the locations; however, landcover classes such as rainforest and desert were not included in this dataset.

Figure 4-1 illustrates the high-resolution imagery used in the analysis, showcasing their diverse characteristics and geographical features. The figure also presents the manually derived water polygons used for accuracy calculations of each surface water map generated from S1SAR and S2MSI imagery. The dashed line on each of the images represents the split of training and testing areas for the machine learning classifiers. The solid lines represent the analysis extents.

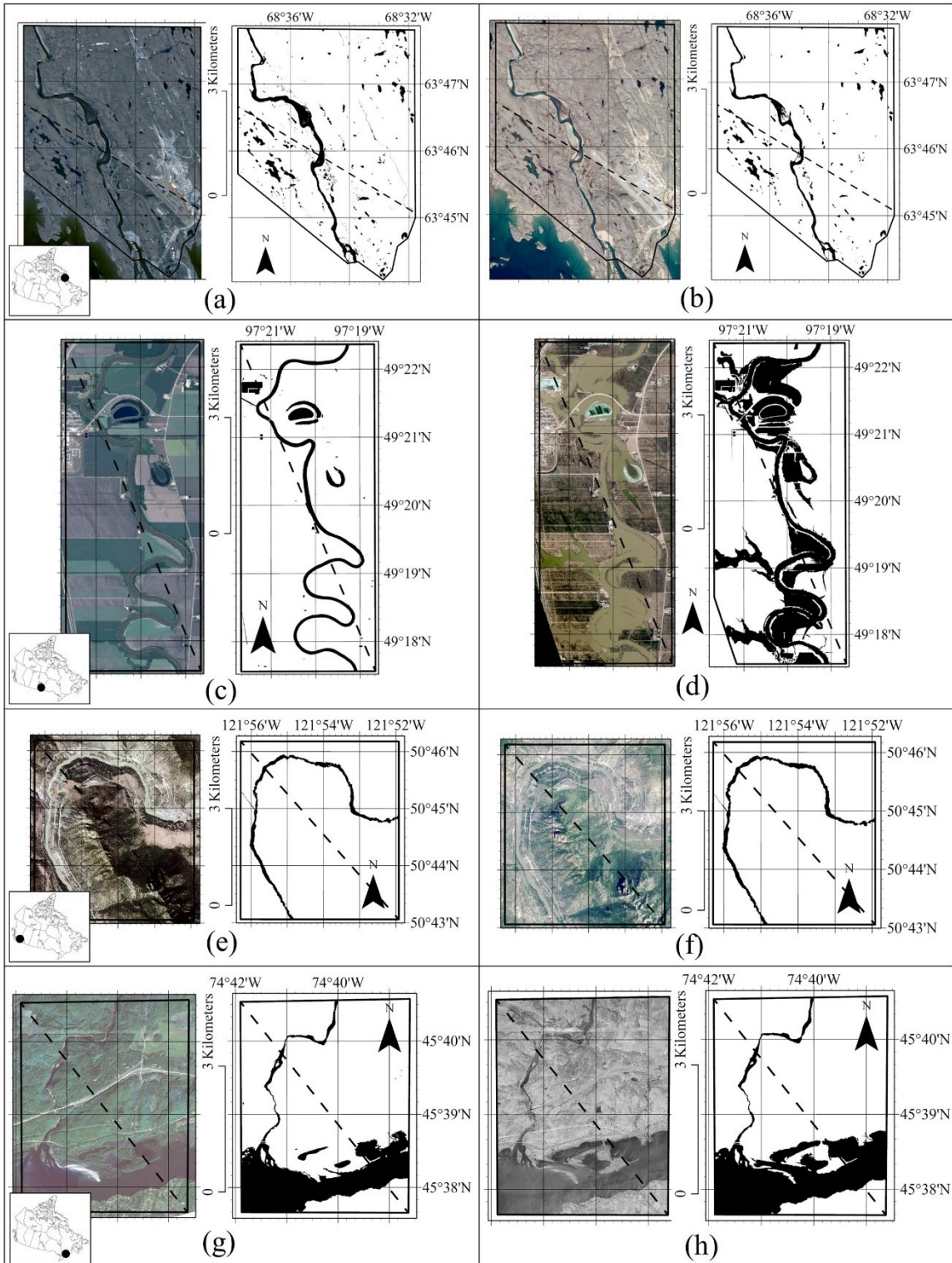


Figure 4-1: True colour high resolution satellite imagery and manually derived water polygons used for validation for (a) Area 1A Sylvia Grinnell River, (b) Area 1B Sylvia Grinnell River, (c) Area 2A Red River, (d) Area 2B Red River, (e) Area 3A Fraser River,

(f) Area 3B Fraser River, (g) Area 4A Rivière-Rouge, and (g) Area 4B Rivière-Rouge. For Areas 1 and 3, the top half of the image was used for training. For Areas 2 and 4, the bottom half of the image was used for training.

Additionally, the projected local incidence angles for the S1SAR imagery and the Sun zenith angles for the S2MSI imagery are presented in Table 4-2. These data were collected from the imagery metadata. As shown, some notable differences exist between the local incidence angles of the four locations as well as between the two seasons at each location. In particular, the incidence angles of Areas 2A and 2B as well as Areas 3A and 3B are different, and the impact of the different incidence angles on the accuracy of the surface water maps will be evaluated.

Table 4-2: S1SAR local incidence angles and S2MSI Sun zenith and viewing incidence angles.

Image Code	S1SAR Mean Projected Local Incidence Angle	S2MSI Local Sun Zenith Angle	S2MSI Viewing Incidence Zenith Angle
Area 1A	46	44	4.1
Area 1B	46	55	6.1
Area 2A	35	28	4.4
Area 2B	43	44	4.3
Area 3A	47	46	3.0
Area 3B	41	32	3.0
Area 4A	40	46	9.9
Area 4B	40	25	3.5

4.3 Methods

4.3.1 Methodology Framework and Comparison Basis

The Critical Success Index (CSI) is commonly used as a verification statistic for flood modelling. The CSI was computed for each classified map to assess the performance of the associated classification approach, and as a basis to compare

classification approaches to one another. The CSI was calculated using the following equation:

$$[4-1] \text{CSI} = \frac{A}{A+B+C}$$

where A were the correct predictions made by the model (in km²), or matching area, B were the overpredictions by the model (in km²), or commission errors, and C were the underpredictions by the model (in km²), or omission errors (Lim and Brandt, 2019). The CSI metric accounts for the pixels that were classified successfully (i.e., the matching area), the land pixels that were misclassified as water (i.e., the commission error), and the water pixels that were misclassified as land (i.e., omission error). The CSI approach was chosen in this study in addition to the typical Overall Accuracy (OA) and Kappa Coefficient approaches. The OA and Kappa Coefficient were calculated using the following equations:

$$[4-2] \text{OA} = \frac{TP+TN}{TP+FP+TN+FN}$$

$$[4-3] \kappa = \frac{2 \times (TP \times TN - FN \times FP)}{(TP+FP) \times (FP+TN) \times (TP+FN) \times (FN+TN)}$$

where TP is the number of true positive samples, TN is the number of true negative samples, FP is the number of false positive samples, and FN is the number of false negative samples. For each of the eight images, 1000 randomly generated points were used to compute OA and Kappa. Comparatively, the OA and Kappa approaches utilize random point sampling, whereas the CSI is a global approach. The global approach allowed for identification of spatially small errors (e.g., mountain shadows, improperly classified shorelines, etc.) that that OA and Kappa approach may not have been able to capture. To calculate the matching area, commission error, omission error, and accuracy statistics for OA and Kappa, the surface water maps derived from S1SAR and S2MSI imagery were compared to validation surface water maps manually delineated from the high-resolution satellite imagery listed in Table 4-1 and presented in Figure 4-1. The validation surface water maps are assumed to have negligible error. To evaluate the statistical significance of the results, analysis of variance (ANOVA) tests were performed on the eight images and the two fixed factors were the classification method and the image input (multispectral band or polarization). The response variable used was the CSI. The α used for the ANOVA test was 0.05. Three p values were derived for each comparison based on the ANOVA framework: the p value describing the significance of the method used, the p value describing the significance of the imagery input used, and the p value describing the significance of the interaction between the method and imagery input used. The null hypothesis tested was that the mean CSIs of the surface water maps were the same when varying the classification method and the classification input. For example, upon comparing the CSIs of the surface water maps derived from S1SAR

imagery to those derived from S2MSI imagery, the p value describing the significance of the imagery input was used to determine the likelihood that the mean CSI from the S1SAR imagery is the same as the mean CSI from the S2MSI imagery.

The methodology framework for this study is presented in Figure 4-2. The images for each area were first prepared for analysis in SeNtinel Application Platform (SNAP) software, and then classification was performed via the following machine learning techniques: Support Vector Machine (SVM), Random Trees (RT), Maximum Likelihood Classifier (MLC), and K-Nearest Neighbour (KNN). Simple machine learning methods were selected for comparison, rather than comparison via deep learning methods, for two reasons. The first is that because of the large variety of deep learning algorithms available for image classification, the scope of the study was focused by selecting a few, widely applied methods. Many machine learning algorithms exist to classify image pixels, especially considering the various neural network algorithms that have been developed in recent years. Neural networks allow for the generation of multiple layers of relationships between the imagery inputs and the output classified images, most likely improving the accuracy of the final classified image. However, although complexity is increased in these algorithms, the successful binary classification of pixels into land or water might not be improved with increasing algorithm complexity, as shown in Manaf et al. (2016) and Li et al. (2022). The second is that the main intent of this study was not to compare image classification methods and rather to test the imagery inputs on the classification accuracy. Multiple classification methods were included in this study only to understand the uniformity of comparisons across different algorithms. The resulting surface water maps were compared against high-resolution validation data for accuracy evaluation. Each step of the image processing and evaluation is explained further in the following sections.

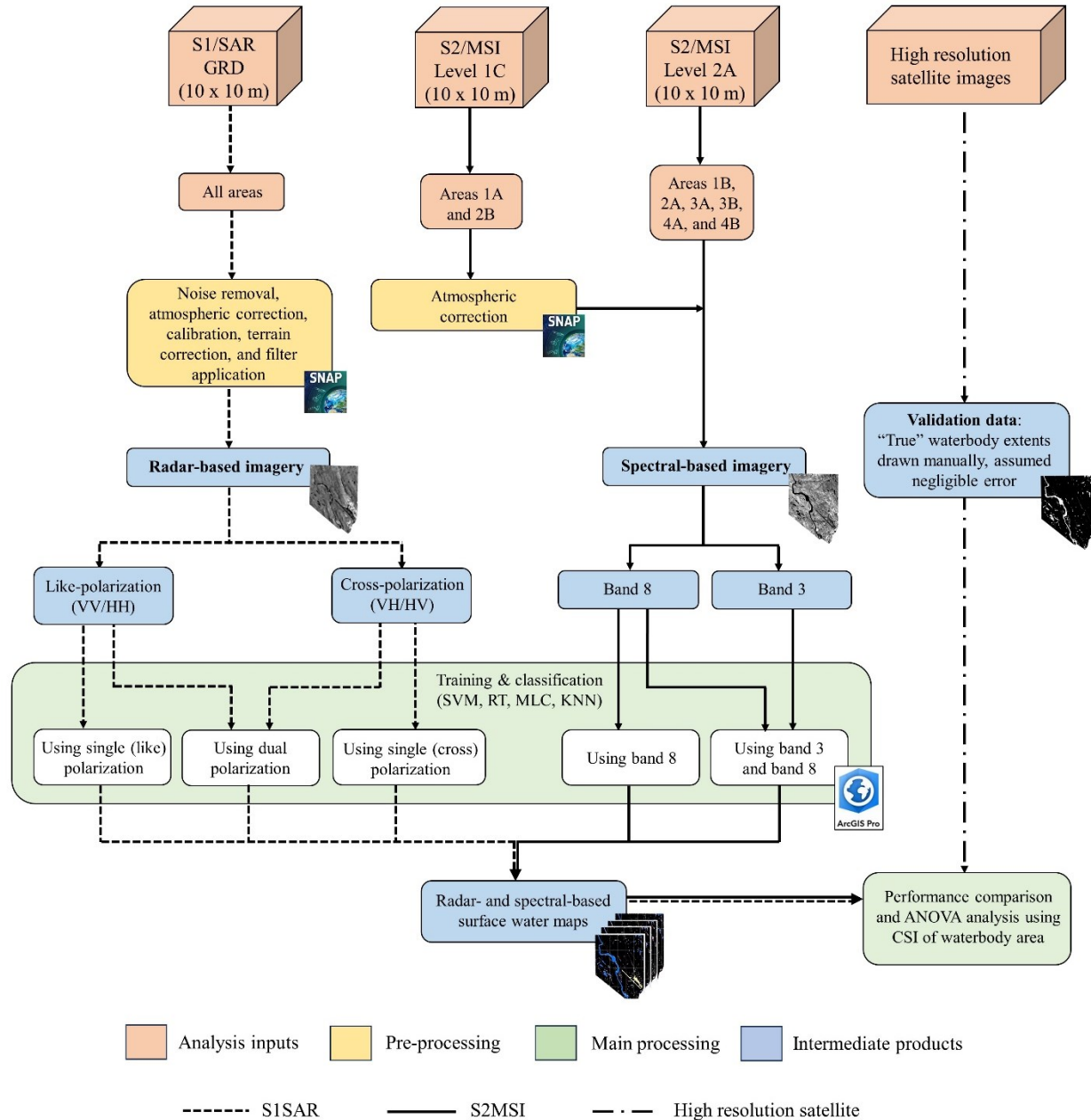


Figure 4-2: Study methodology framework.

4.3.2 Image Preparation

As the images for the Area 1A and Area 2B study locations were taken before 2019/01/01, the S2MSI image was only available in Level 1C processing, where the top of atmosphere (TOA) reflectance was not yet converted to bottom of atmosphere (BOA) reflectance. Thus, the images were converted from TOA to BOA reflectance using the Sen2Cor tool in SNAP (Mueller-Wilm et al., 2020). All S2MSI images for the other six locations were available in Level 2A processing. The multispectral bands 3 and 8 were used in this analysis, both of which have a 10 x 10 m resolution. No cloud masking was

required for these images, as the dates of the imagery were chosen to coincide with cloud-free conditions.

S1SAR imagery is available in both Single Look Complex (SLC) and Ground Range Detected (GRD) processing levels, where the SLC image contains both amplitude and phase information and the GRD image is projected to ground range using an ellipsoid model. Thus, phase information is lost and speckle is reduced for GRD products (Bourbigot et al., 2016). S1SAR GRD products were used in this analysis, and the products were downloaded in IW swath mode for all study locations. The following steps were performed for the preparation of the S1SAR imagery in SNAP: thermal noise removal, application of orbit file, border noise removal, calibration, Lee-Sigma speckle filtering (15x15 window size), terrain correction with Range Doppler terrain correction via Nearest Neighbour, conversion of linear to decibels for all bands, and median filtering (non-linear and 3x3). For the terrain correction, the 3 arc-second Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) was used for the Areas 2, 3, and 4, but the Copernicus DEM 30m (from 0.75 to 3 arc-seconds, depending on the longitude) was used for Area 1 as the SRTM DEM was not available in the Arctic. The pre-processing steps for both the S1SAR and S2MSI images are shown in yellow in Figure 4-2.

4.3.3 Generation of Surface Water Maps

Surface water mapping of the S1SAR and S2MSI images for the four locations was conducted with four commonly used supervised machine learning techniques: SVM, RT, MLC, and KNN. Four techniques were used to minimize the influence of classification technique on the S1SAR and S2MSI imagery comparison findings. The methodology framework is presented in Figure 4-2 to illustrate the processing steps included in the analysis, illustrated in green. For consistency of comparison and ease of processing, the image classification was completed using the default machine learning classification tools available from ArcGIS Pro Version 3.03. These readily available ArcGIS tools are employed by a wide variety of users with various levels of imagery processing experience. For the SVM algorithm, ArcGIS Pro uses nonlinear radial basis function kernels and does not assume the samples follow a normal distribution (Li et al., 2022). The default value of 1000 training samples per class was used for the SVM technique. Default numbers of 50 maximum trees, 30 maximum tree depth, and 1000 samples per class were used for the RT function in ArcGIS, which uses the random forest algorithm developed by Breiman (2001) and is resistant to overfitting. The default settings for the MLC technique were used, and default values of 1 neighbour and 1000 samples per class were used for the KNN technique in ArcGIS Pro. Adjustment of these parameters to obtain an optimized set of parameters was not considered in this work, as comparison of the methods to understand the most optimal method was not within the scope of this work. Rather, the

parameters were kept fixed between each comparison to understand the effect on the imagery inputs (e.g., polarization, multispectral band, etc.) instead.

Each study location was divided into two halves: one half was used to train each technique, and the other half was used to evaluate the classification accuracy. Consequently, the training/validation ratio was 50/50. The eight study images were divided strategically in an attempt to include the image characteristics unique to each location in both the training and validation areas, such as built infrastructure, high albedo surfaces, shadows, and snow/ice. The impact of the classification input on final quality of the resulting surface water map was analyzed by varying the training input. The S1SAR imagery was trained with the like-polarization (VV or HH), the cross-polarization, and the dual polarization (VV and VH or HV and HH). The impact of adding the green band of multispectral imagery for S2MSI was analyzed by training the classification with both just band 8 (i.e., only NIR) and with band 3 and band 8 (i.e., both green and NIR). Ultimately, four comparisons were performed:

- Comparison of like-polarization to cross-polarization
- Comparison of single polarization (best of like- or cross-polarization) to dual polarization
- Comparison of band 8 to band 3+8
- Comparison of S1SAR (best of dual or single polarization) to S2MSI (best of band 8 or band 3+8)

A trained classification file was produced as the result of training the algorithms using the training portion of the various S1SAR or S2MSI images and ground-truth high-resolution satellite-derived polygons (in Figure 4-1). Then, the trained classification files for each scenario were applied to the validation portion of each S1SAR or S2MSI image to classify the image into water and land pixels. This is how the surface water maps were generated.

4.4 Results

For each of the four comparisons (like-polarization vs. cross-polarization, dual polarization vs. single polarization, etc.), a total of 32 surface water maps were derived from the eight images using four different classification methods. Five of the surface water mapping results are presented in Figure 4-3 for Area 2A using the SVM classification technique. To illustrate a visual interpretation of the CSI metric, the CSIs of the five surface water maps in Figure 4-3 from left to right are 0.58 (VV+VH), 0.36 (VV), 0.38 (VH), 0.88 (Band 8), and 0.86 (Band 3 + Band 8). The statistical metrics of each classification are also presented in Table 4-3. The location with the most accurate surface water maps was Area 4 with mean CSIs of 0.75 and 0.73 for Area 4A and 4B, respectively. The location with the least accurate surface water maps was Area 3 with mean CSIs of 0.21 and 0.22 for Areas 3A and 3B, respectively. It was observed that the topographic

correction of the canyon and mountains in the Area 3A and 3B S1SAR images created distortion of the river, narrowing it so that a continuous water extent could not be derived. This was also observed at the relatively higher relief areas in the Area 1A and 1B S1SAR images, where the distortion caused by topographical correction of the radar imagery removed many of the shoreline water pixels. The mean CSIs for Area 1A and 1B were 0.28 and 0.37, respectively. Finally, Area 2A (presented in Figure 4-3) and 2B resulted in mean CSIs of 0.48 and 0.59, respectively.

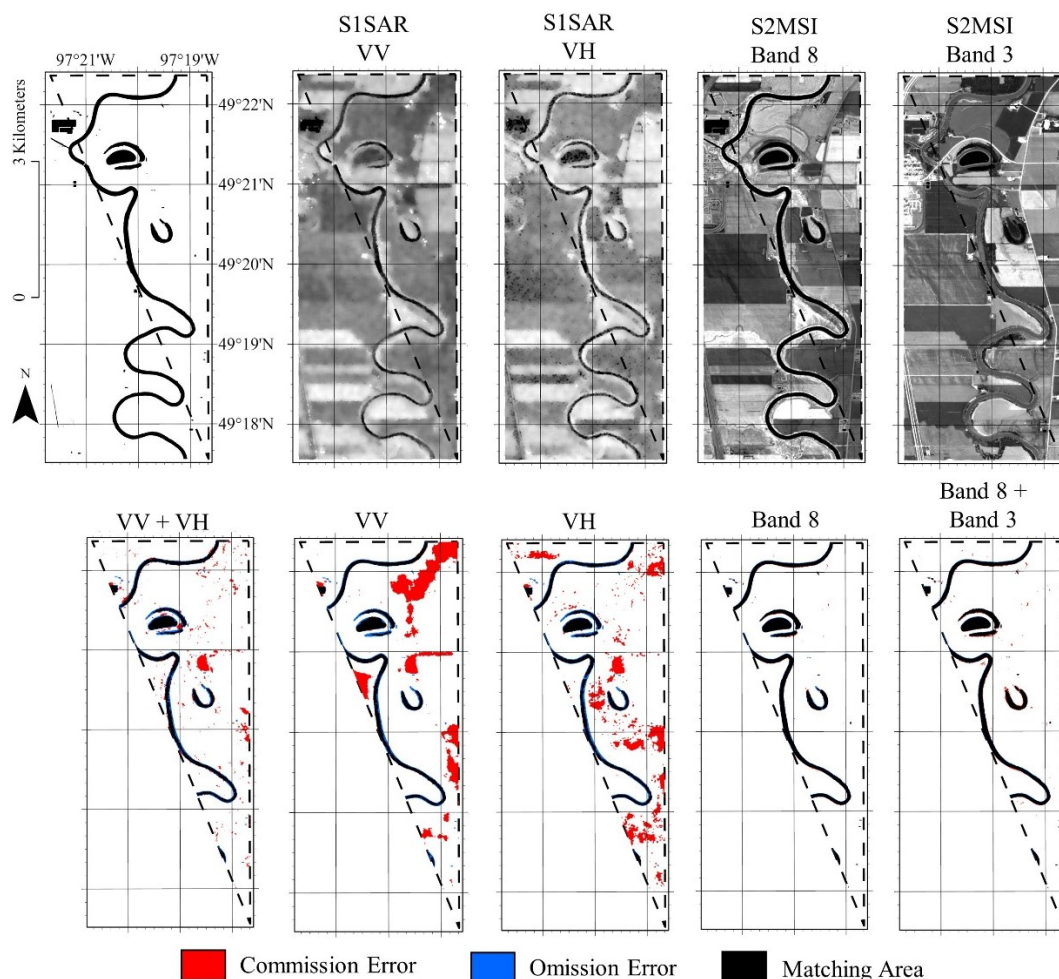


Figure 4-3: Area 2A results using SVM.

The classification technique that, on average, produced the highest accuracy surface water maps was SVM with a mean CSI of 0.55. Following after SVM in order of highest to lowest mean CSI was RT with 0.49, KNN with 0.39, and MLC with 0.39. Both SVM and RT techniques were observed to produce the least amount of speckle in the resulting surface water maps. The MLC technique produced the greatest range of CSI results with a standard deviation of 0.32. Following MLC, the order of standard deviation of CSIs from highest to lowest was SVM with 0.30, RT with 0.29, and KNN with 0.26. The MLC technique produced poor results for the S1SAR dual polarization configuration,

where the addition of the second polarization consistently caused the tool to classify nearly the entire image as water. The same was true for the addition of band 3 for the MLC technique when classifying S2MSI imagery, but the effect of classifying the entire image as water was not consistent across the study locations. This inconsistency stems from the MLC tool in ArcGIS Pro considering only the class means of the “primary” band of imagery, and when a second band of imagery is added to the classification, the class means are not adjusted. Thus, if the second band of imagery significantly changes the means of the classes, as is the case for Area 2B, misclassification occurs.

Table 4-3: Statistical metrics of the classified images

Test Site	Classification Method	Imagery Input	Overall Accuracy	Kappa Coefficient	CSI
Area 1A, Sylvia Grinnell River (July, High Flow)	SVM	HH+HV	0.842	0.316	0.222
		HH	0.823	0.286	0.213
		HV	0.811	0.266	0.193
		Band 8	0.959	0.777	0.607
		Band 3+8	0.954	0.758	0.616
	RT	HH+HV	0.727	0.186	0.160
		HH	0.760	0.206	0.164
		HV	0.695	0.129	0.137
		Band 8	0.939	0.693	0.499
		Band 3+8	0.926	0.657	0.513
	MLC	HH+HV	0.094	0.000	0.094
		HH	0.784	0.253	0.195
		HV	0.803	0.254	0.187
		Band 8	0.940	0.704	0.546
		Band 3+8	0.848	0.457	0.335
	KNN	HH+HV	0.599	0.097	0.128
		HH	0.610	0.094	0.127
		HV	0.576	0.074	0.113
		Band 8	0.755	0.297	0.237
		Band 3+8	0.848	0.460	0.360
Area 1B, Sylvia Grinnell River (August, Low Flow)	SVM	HH+HV	0.840	0.294	0.234
		HH	0.801	0.235	0.211
		HV	0.767	0.218	0.166
		Band 8	0.982	0.872	0.736
		Band 3+8	0.982	0.872	0.737
	RT	HH+HV	0.787	0.227	0.195
		HH	0.730	0.146	0.165
		HV	0.700	0.161	0.128
		Band 8	0.978	0.845	0.701
		Band 3+8	0.983	0.880	0.713
	MLC	HH+HV	0.071	0.000	0.071
		HH	0.812	0.250	0.218
		HV	0.791	0.232	0.170
		Band 8	0.987	0.902	0.781
		Band 3+8	0.960	0.582	0.451
	KNN	HH+HV	0.688	0.140	0.133
		HH	0.680	0.122	0.140
		HV	0.619	0.104	0.110
		Band 8	0.965	0.777	0.603
		Band 3+8	0.972	0.810	0.667

Area 2A, Red River (June, Low Flow)	SVM	VV+VH	0.953	0.671	0.576
		VV	0.876	0.367	0.362
		VH	0.899	0.449	0.380
		Band 8	0.992	0.938	0.882
		Band 3+8	0.991	0.931	0.864
	RT	VV+VH	0.886	0.439	0.380
		VV	0.802	0.251	0.254
		VH	0.820	0.282	0.255
		Band 8	0.981	0.860	0.763
		Band 3+8	0.992	0.939	0.852
	MLC	VV+VH	0.071	0.000	0.089
		VV	0.863	0.344	0.337
		VH	0.877	0.391	0.339
		Band 8	0.987	0.903	0.842
		Band 3+8	0.992	0.939	0.872
	KNN	VV+VH	0.745	0.199	0.227
		VV	0.725	0.167	0.199
		VH	0.712	0.165	0.171
		Band 8	0.899	0.511	0.451
		Band 3+8	0.937	0.645	0.546
Area 2B, Red River (April, Flood Flow)	SVM	VV+VH	0.903	0.772	0.732
		VV	0.878	0.712	0.689
		VH	0.811	0.565	0.548
		Band 8	0.869	0.710	0.708
		Band 3+8	0.971	0.934	0.897
	RT	VV+VH	0.885	0.732	0.704
		VV	0.842	0.643	0.607
		VH	0.775	0.502	0.490
		Band 8	0.864	0.691	0.674
		Band 3+8	0.976	0.945	0.892
	MLC	VV+VH	0.315	0.000	0.316
		VV	0.853	0.668	0.642
		VH	0.776	0.511	0.525
		Band 8	0.699	0.436	0.506
		Band 3+8	0.492	-0.304	0.009
	KNN	VV+VH	0.777	0.529	0.574
		VV	0.786	0.540	0.558
		VH	0.698	0.372	0.435
		Band 8	0.713	0.371	0.413
		Band 3+8	0.972	0.936	0.858
Area 3A, Fraser River (September, Lower Flow)	SVM	VV+VH	0.809	0.198	0.136
		VV	0.650	0.062	0.064
		VH	0.767	0.118	0.096
		Band 8	0.881	0.312	0.230
		Band 3+8	0.990	0.860	0.795
	RT	VV+VH	0.817	0.207	0.153
		VV	0.705	0.068	0.061
		VH	0.767	0.118	0.088
		Band 8	0.894	0.333	0.239
		Band 3+8	0.988	0.836	0.784
	MLC	VV+VH	0.966	0.000	0.000
		VV	0.644	0.060	0.064
		VH	0.688	0.096	0.085
		Band 8	0.903	0.347	0.255
		Band 3+8	0.871	-0.053	0.000
	KNN	VV+VH	0.772	0.169	0.107

Area 3B, Fraser River (July, Higher Flow)	SVM	VV	0.733	0.068	0.058
		VH	0.742	0.108	0.076
		Band 8	0.874	0.207	0.185
		Band 3+8	0.989	0.848	0.803
		VV+VH	0.919	0.416	0.294
		VV	0.638	0.038	0.091
	RT	VH	0.638	0.038	0.147
		Band 8	0.951	0.559	0.382
		Band 3+8	0.975	0.735	0.560
		VV+VH	0.917	0.417	0.295
		VV	0.702	0.038	0.057
		VH	0.702	0.038	0.126
	MLC	Band 8	0.948	0.550	0.350
		Band 3+8	0.980	0.777	0.590
		VV+VH	0.962	0.000	0.000
		VV	0.599	0.049	0.061
		VH	0.599	0.049	0.100
		Band 8	0.944	0.531	0.362
	KNN	Band 3+8	0.927	-0.038	0.001
		VV+VH	0.825	0.230	0.154
		VV	0.715	0.042	0.056
		VH	0.715	0.042	0.102
		Band 8	0.892	0.355	0.204
		Band 3+8	0.962	0.643	0.435
Area 4A, Rivière-Rouge (September, Low Flow)	SVM	VV+VH	0.975	0.862	0.828
		VV	0.978	0.874	0.816
		VH	0.979	0.885	0.852
		Band 8	0.992	0.957	0.898
		Band 3+8	0.992	0.956	0.909
		VV+VH	0.974	0.859	0.826
	RT	VV	0.947	0.732	0.640
		VH	0.954	0.776	0.679
		Band 8	0.984	0.916	0.826
		Band 3+8	0.991	0.952	0.893
		VV+VH	0.115	0.002	0.103
		VV	0.978	0.874	0.811
	MLC	VH	0.977	0.873	0.849
		Band 8	0.984	0.916	0.892
		Band 3+8	0.991	0.952	0.884
		VV+VH	0.940	0.721	0.585
		VV	0.936	0.697	0.575
		VH	0.941	0.724	0.607
	KNN	Band 8	0.971	0.857	0.696
		Band 3+8	0.974	0.871	0.773
Area 4B, Rivière-Rouge (June, High Flow)	SVM	VV+VH	0.975	0.884	0.797
		VV	0.974	0.876	0.771
		VH	0.966	0.846	0.758
		Band 8	0.990	0.952	0.921
		Band 3+8	0.990	0.952	0.917
		VV+VH	0.965	0.844	0.761
	RT	VV	0.944	0.757	0.682
		VH	0.933	0.728	0.631
		Band 8	0.984	0.923	0.876
		Band 3+8	0.988	0.942	0.908
		VV+VH	0.122	0.000	0.116
		VV	0.952	0.788	0.705

KNN	VH	0.965	0.842	0.754
	Band 8	0.990	0.952	0.921
	Band 3+8	0.989	0.947	0.907
	VV+VH	0.909	0.652	0.564
	VV	0.909	0.646	0.382
	VH	0.926	0.708	0.600
	Band 8	0.978	0.897	0.811
	Band 3+8	0.975	0.888	0.823

4.4.1 S1SAR, Like-Polarization vs. Cross-Polarization

Fourteen of the 32 results performed better with the like-polarization input compared to 15 of the 32 results for the cross-polarization input, as illustrated in Figure 4-4. Three of the results produced CSIs within 0.01 of each other (shown as hatched bars in Figure 4-4) and 24 of the results produced CSIs within 0.05 of each other (shown as asterisks in Figure 4-4) for the like- and cross-polarization input comparison. The p values from the ANOVA test are shown in Figure 4-4. The p value indicating the significance of the polarization is 0.973, much greater than 0.05, indicating that there is no significant difference between the mean CSI of the surface water maps derived from the like-polarization versus the cross-polarization. Likewise, both the p values for the method and the interaction between method and polarization are greater than 0.05. The p values for the ANOVA tests excluding the MLC method are also shown in Figure 4-4 for consistency between the four comparisons. As previously explained, the MLC method can influence the outcome of the ANOVA tests for the other comparisons due to how the class means are selected in the ArcGIS MLC tool. However, for this comparison, exclusion of the MLC method does not change the outcome of the significance of the p values. This result is expected as only one imagery input (i.e., one polarization) was used in this comparison, and the bias of the MLC technique is only introduced when applying the method on dual polarization or multiple bands of imagery.

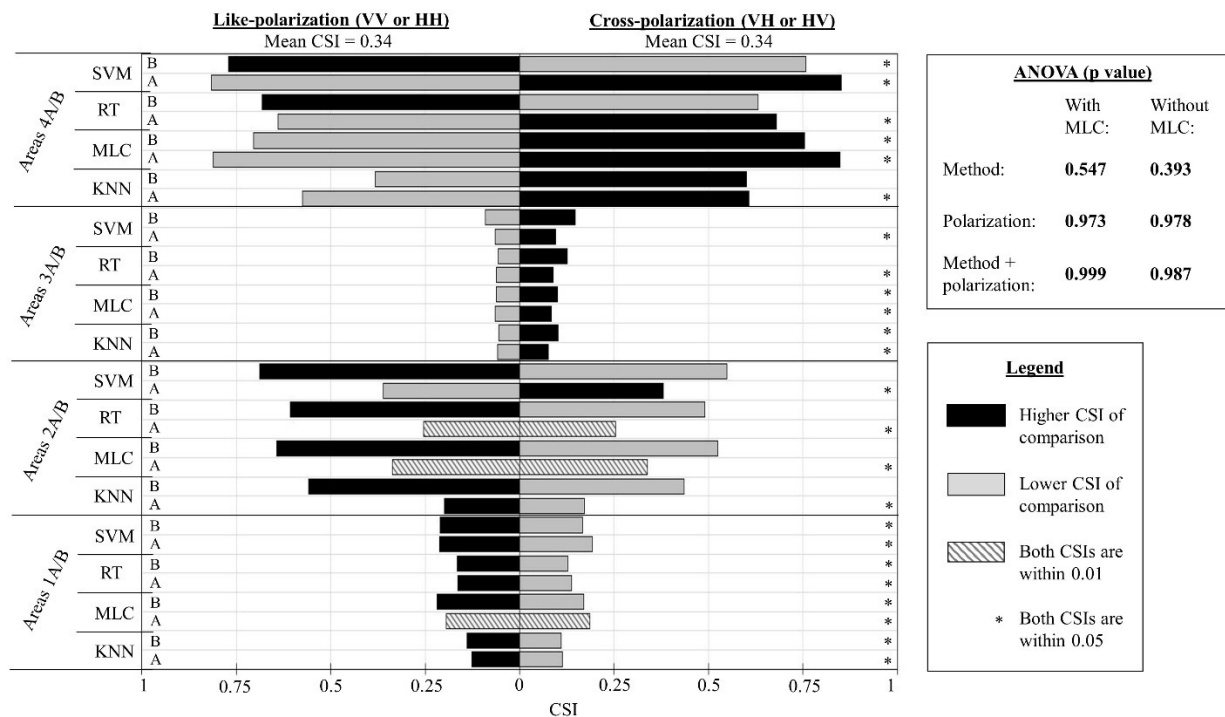


Figure 4-4: Quality of surface water maps and ANOVA analysis derived from like-polarization and cross-polarization of S1SAR imagery across the eight image areas based on the CSI metric.

The superiority of like- or cross-polarization across each location was reasonably consistent. Like-polarization performed better for surface water mapping in Area 1 for both 1A and 1B, although both polarizations produced poor quality surface water maps. Like-polarization also performed better for surface water mapping in Area 2 where the like-polarization classified the water and shoreline pixels more accurately than cross-polarization. Cross-polarization performed better consistently for Area 3, where the Area 3A image was not able to be classified accurately into a surface water map by either of the polarizations, and the Area 3B image had fewer misclassifications caused by shadows from the cross-polarization and the separation of water to land pixels was more accurate. Cross-polarization performed generally better at surface water mapping for Area 4 where commission errors were reduced and more of the water pixels were correctly classified.

4.4.2 S1SAR, Single Polarization vs. Dual Polarization

Seventeen of the 32 results performed better with the dual polarization input compared to 11 of the 32 results for the single polarization input, as shown in Figure 4-5. Four of the results produced CSIs within 0.01 of each other (shown with hatched bars in Figure 4-5), and 15 of the results produced CSIs within 0.05 of each other (shown with asterisks in Figure 4-5) for the dual and single polarization input comparison. The p value describing the significance of the difference in polarization was 0.577, indicating that there is no significant difference between the mean CSI of the surface water maps derived from

the single polarization versus the dual polarization. As a test, because the MLC technique produced consistently poorer results for dual polarization due to considering only the class means of the primary band of imagery, the ANOVA was performed again with the MLC population removed. The resulting p value was 0.511, indicating that even among only RT, SVM, and KNN techniques, the mean CSI derived from single polarization is not likely to be different from the mean CSI derived from dual polarization. The p values comparing the performances of the methods used and the interactions between methods and polarizations were also not greater than 0.05 both with and without the MLC method.

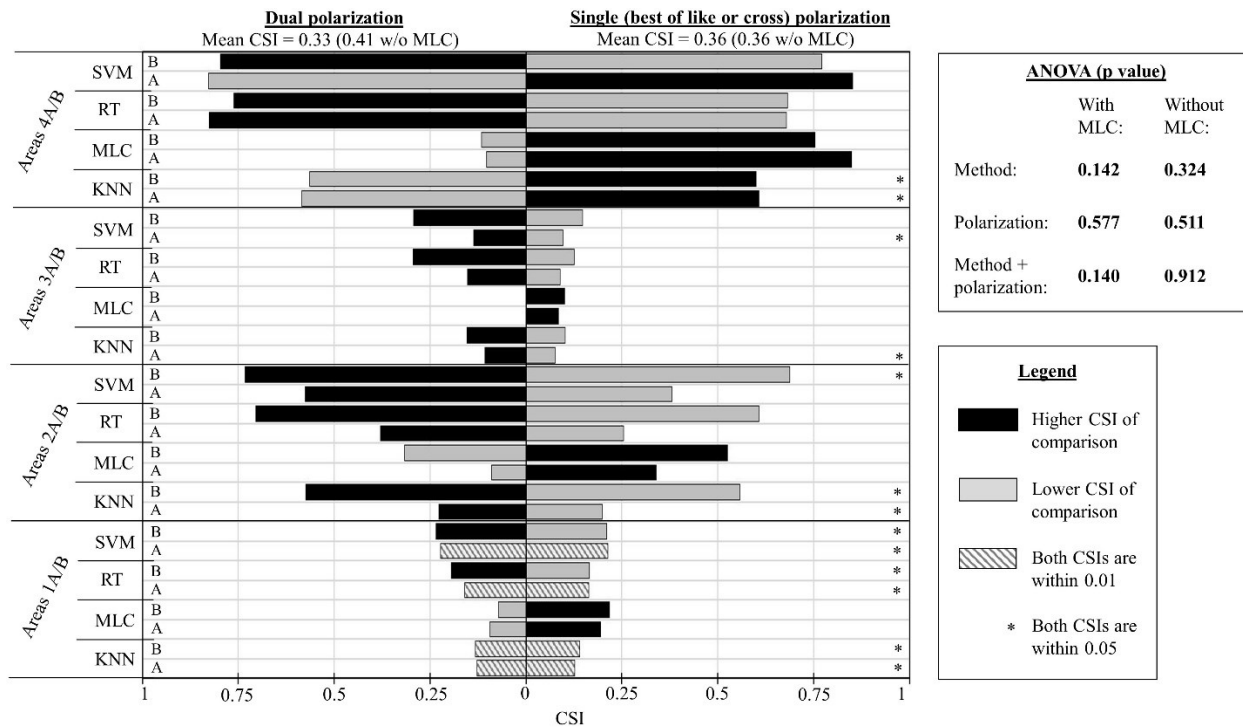


Figure 4-5: Quality of surface water maps and ANOVA analysis derived from one polarization (best result of single polarization or dual polarization) and both polarizations of S1SAR imagery across the eight image areas based on the CSI metric.

The resulting accuracy of the surface water maps derived from dual polarization compared to single polarization was less consistent across the locations compared to like- and cross-polarization. The comparison was also not consistent across the four classification techniques at each location. This type of contrariety is illustrated in Figure 4-6 where the difference between the surface water maps derived from RT are compared to the surface water maps derived from SVM for Area 4A. The use of dual polarization when applying the RT technique reduced the speckle, resulting in a reduced commission error, whereas the use of dual polarization for the SVM technique caused the shorelines of the Ottawa River (lower right area of image) to become poorly defined, increasing the omission error.

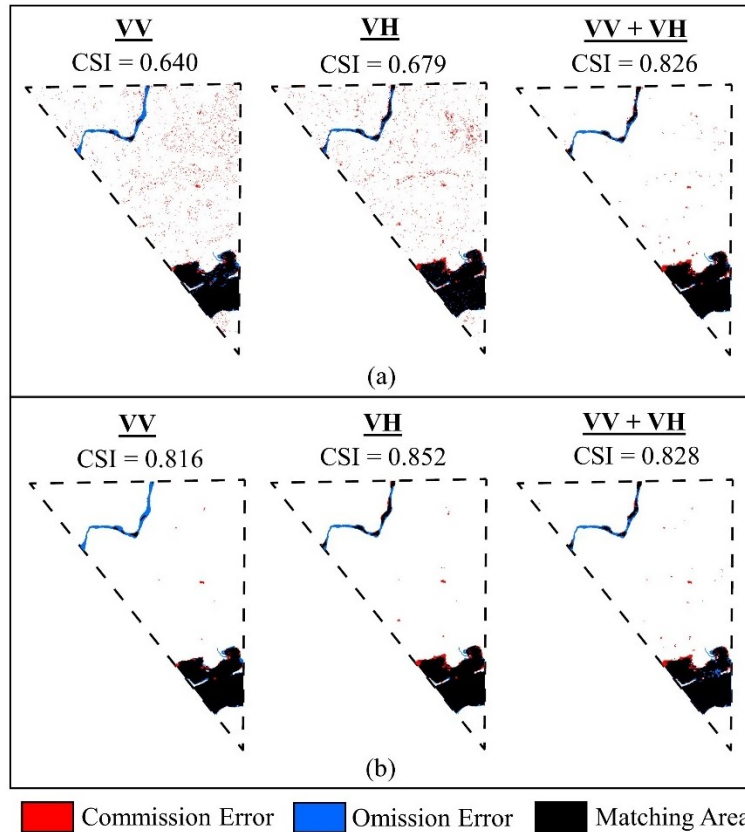


Figure 4-6: Surface water maps and associated CSIs derived from single polarizations (VV and VH) and dual polarization (VV + VH) of S1SAR imagery using the (a) RT and (b) SVM techniques.

The addition of the secondary polarization reduced the commission error in the Area 4A and 4B images (due to decreased speckle), Area 2A and 2B images (due to reduced size of crop areas misclassified as water), and Area 3A and 3B images (due to reduced size of mountain shadows misclassified as water). The effect on the accuracy of waterbody shorelines was not consistent across the image areas. In the Area 2A and 4A images, the use of dual polarization did not define the shoreline as well as the single polarization. On the other hand, in the Area 3B and 4B images, the use of dual polarization improves the shoreline delineation.

Previous literature has found dual polarization to be better at classifying water areas with vegetation than single polarization (Ireland et al., 2015). Areas 2 and 4 contain some vegetated shorelines, and thus observations were collected for these four images to test this theory. In the Area 2A image, the dual polarization input caused the vegetated oxbow lake shorelines to become irregular, and the single polarization created a smoothed boundary that better represented the actual shoreline. Visual observation of the flooded shoreline in the Area 2B image revealed that dual polarization better represented the actual shoreline; thus, dual polarization may be more successful at

extracting flooded shorelines compared to single polarization. In the Area 4A image, the dual polarization input misclassified some shallow water pixels as land near the vegetated shorelines with the SVM technique, but no noticeable differences were observed for the other methods. Finally, there was no difference in the quality of the derived shoreline boundary for the vegetated shorelines in the Area 4B image.

4.4.3 S2MSI, One Band vs. Two Bands

Twenty-one of the 32 results performed better with the bands 3 and 8 input compared to seven of the 32 results for the band 8 only input. Four of the results produced CSIs within 0.01 of each other (shown as hatched bars in Figure 4-7) and 12 of the results produced CSIs within 0.05 of each other (shown with asterisks in Figure 4-7) for the dual and single polarization input comparison. The p value describing the significance of the multispectral band input was 0.276, higher than 0.05, when including MLC. However, upon excluding MLC from the ANOVA analysis due to the bias it introduces by only considering the primary band's class means, the p value was 0.010, indicating a statistically significant difference in the mean CSI derived from band 8 versus the mean CSI derived from band 3 and band 8. This result suggests that the addition of band 3 improves classification accuracy for S2MSI imagery when applying traditional machine learning techniques. Additionally, upon removal of the MLC method from the sample dataset, the p value for method becomes significant with a change from 0.069 to 0.049, implying that among the SVM, RT, and KNN methods, the selection of the method can influence the quality of the surface water map for S2MSI imagery when using band 8 or bands 3 and 8.

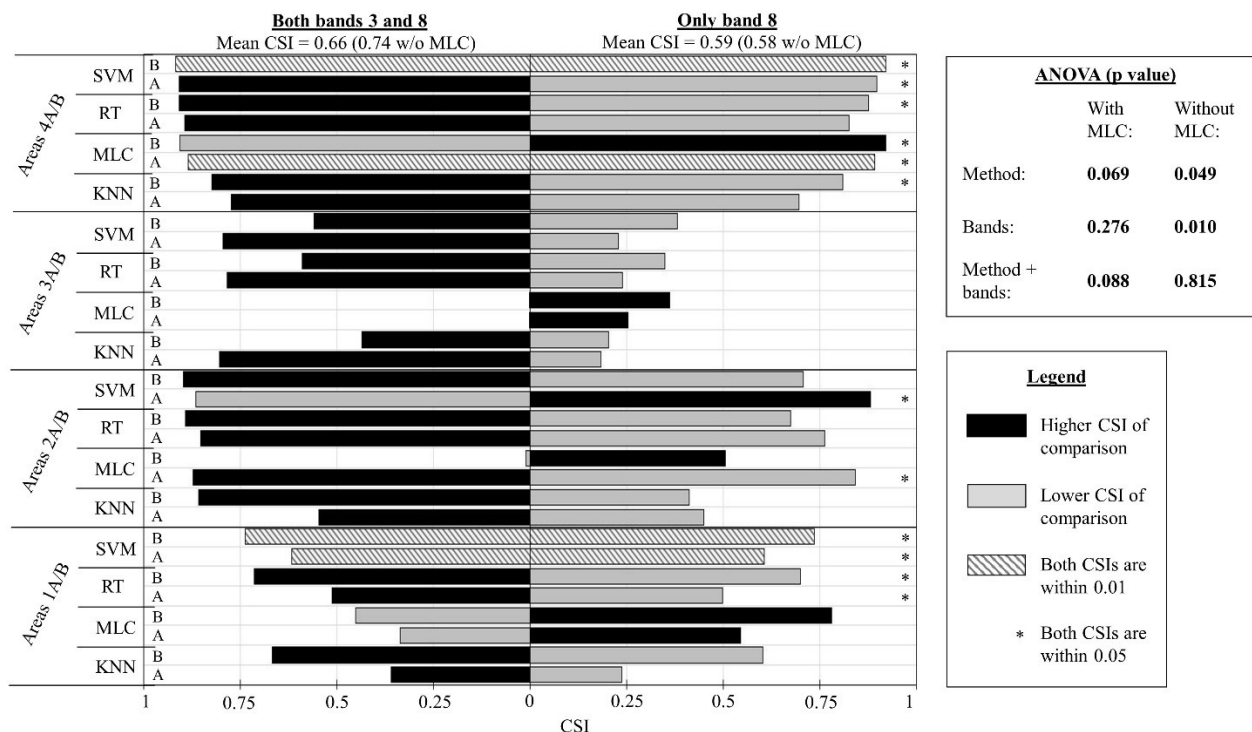


Figure 4-7: Quality of surface water maps and ANOVA analysis derived from one band (NIR band) and two bands (green and NIR band) of S2MSI imagery across the eight image areas based on the CSI metric.

Across the eight images, the addition of band 3 to the classification was visually observed and quantified to improve the accuracy of the surface water maps by reducing the commission error, either by reducing speckle (Areas 2A, 2B, and 4B) or by reducing the size of the error where mountain shadows exist (Areas 3A and 3B). The addition of band 3 also improved the connectivity of the waterbody pixels and the accuracy of the derived shoreline (Areas 3B and 4B). The addition of band 3 did not significantly improve the classification results in the Area 4A image. Contrary results were observed for the Area 1A and 1B images where the results from the MLC method were found to be less accurate with the addition of band 3 due to greater commission errors at the gravel road areas and reduced shoreline accuracy, but the results from the KNN and RT methods showed that the addition of band 3 reduced commission errors due to the runway and improved shoreline accuracy.

4.4.4 S1SAR vs. S2MSI

One of the 32 results performed better with the S1SAR input compared to 31 of the 32 results for the S2MSI input, as illustrated in Figure 4-8. None of the results produced CSIs within 0.01 of each other, and two of the results produced CSIs within 0.05 of each other (shown as asterisks in Figure 4-8) for the S1SAR and S2MSI input comparison. From the ANOVA analysis, the p value for the influence of the imagery input was less than 0.001 both with and without the inclusion of the MLC method in the sample dataset, indicating that there is a statistically significant difference between the mean CSI of the surface water maps derived from the S1SAR input versus the mean CSI of the surface water maps derived from the S2MSI input. With the exception of Area 2B with the MLC technique, shown in Figure 4-8, the CSI value was consistently lower for the S1SAR input, and both misclassification types (commission and omission error) were higher for the S1SAR input. Overall, the disadvantages of the S1SAR imagery compared to S2MSI imagery (i.e., higher error and lower matching area) may impede surface water mapping success with S1SAR imagery. Various causes of misclassification between both the optical and radar imagery were observed and noted, and the S1SAR imagery was found to perform particularly poorly in areas of shadow and high slope. The p value representing the significance of the method on the mean CSI is greater than 0.05, implying that the mean CSI derived from the four methods are not different from each other for the S1SAR and S2MSI imagery inputs used in this analysis. The p value demonstrating the influence of the interaction between the method and imagery input is much greater than 0.05 both with and without the MLC method included in the dataset.

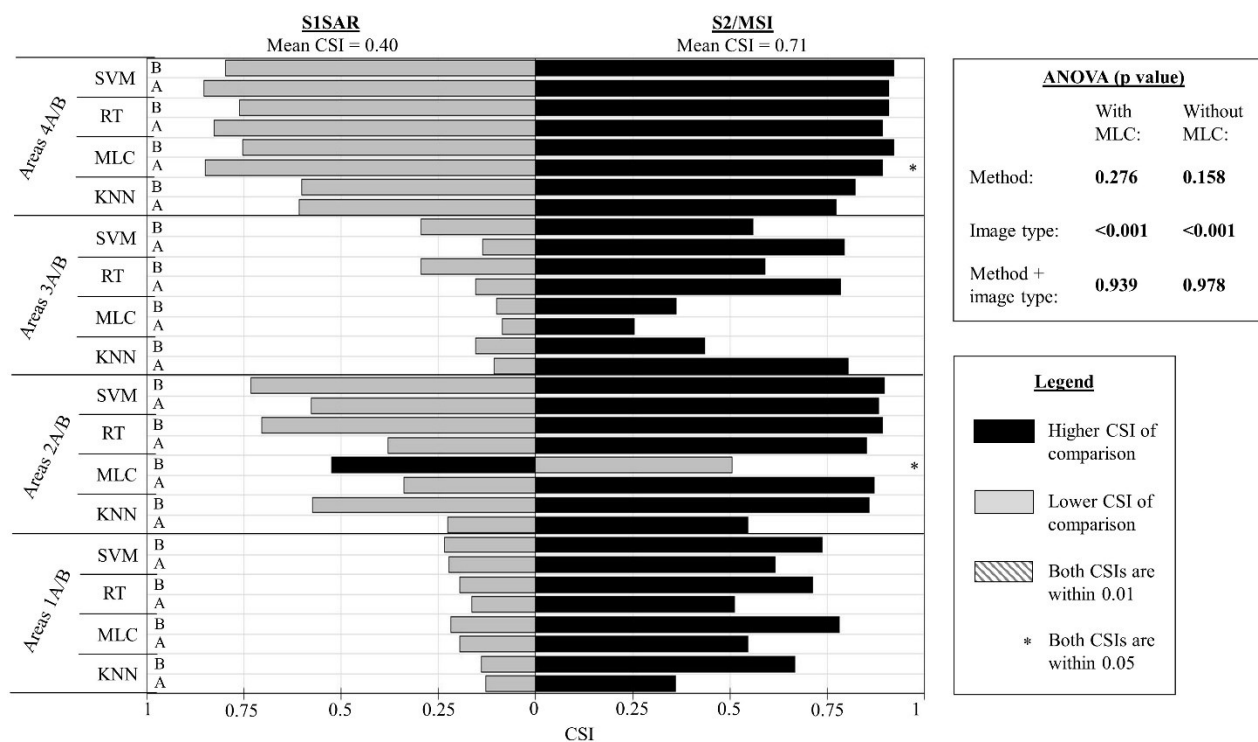


Figure 4-8: Quality of surface water maps and ANOVA analysis derived from S1SAR (best of single, dual, or both polarizations) and S2MSI (best of one band or two bands) imagery across the eight image areas based on the CSI metric.

One advantage of the S1SAR imagery over the S2MSI imagery was that snow and ice in the Area 1A and 2B images could be differentiated from open water using S1SAR imagery but not with S2MSI imagery. Thus, although the accuracy of the surface water map was poorer for the S1SAR imagery compared to S2MSI imagery overall, some advantages exist to retain the usefulness of S1SAR imagery for surface water mapping, depending on the area of interest.

The accuracy of the S1SAR-derived surface water maps tended to trend with the mean local projected incidence angle (shown in Table 4-2), while the accuracy of the S2MSI-derived surface water maps did not trend with the mean Sun zenith angle or the viewing incidence angle. For the study areas where the S1SAR incidence angle varied (Areas 2 and 3, see Table 4-2), the images with the lower incidence angles (Areas 2B and 3B) produced maps with higher CSIs (0.57 and 0.12). Comparatively, the images with higher incidence angles (Areas 2A and 3A) produced maps with lower CSIs (0.30 and 0.08). Area 1 and Area 4 incidence angles did not vary between S1SAR images. The mean CSI between Area 1A and 1B did not change; however, the mean CSI between Area 4A and 4B did change from 0.68 to 0.63 with no change in incidence angle. This trend between S1SAR incidence angle and surface water map CSI is due to the decreased backscatter from land-based surface objects resulting from larger incidence

angles (European Space Agency, 2007). The decreased surface backscatter worsens the division of land and water image classification, as the land pixels become similar intensity to water pixels, creating high commission error.

4.5 Discussion

Although surface water mapping using S1SAR and S2MSI has already been well-established in literature, there remained a research gap. The type of imagery input that produced the highest accuracy surface water map across a wide variety of geographic settings remained unknown. This study further supports the use of S1SAR and S2MSI for surface water mapping by providing recommendations of the polarizations and multispectral bands that should be used for detecting surface water, with consideration of the types of characteristics that may be present in the study image. From this analysis, the superiority of S2MSI satellite imagery over S1SAR imagery for producing accurate surface water maps was evident, although the extent of this superiority varied by location. This result was shown to be true irrespective of the classification method used. Additionally, as the central wavelengths are very similar between the Sentinel-2 series and Landsat multispectral imagery series, the results shown here for multispectral imagery can be applied to Landsat as well. In Area 1 and Area 3, characterized by higher slopes and shadows, S2MSI imagery significantly outperformed S1SAR, with mean CSIs of 0.61 and 0.57, respectively, compared to 0.19 for S1SAR. To overcome the issue of shadows being misclassified as water, a threshold slope (e.g., 5%) can be applied to mask out areas of higher slope, ideally removing these misclassified areas (Vekaria et al., 2022). In addition, terrain correction pre-processing steps that must be applied to S1SAR imagery can cause waterbodies located in steeply sloped areas to appear inaccurate (e.g., artificially narrowed), further contributing to classification inaccuracies in areas with steep slopes. Additionally, the high albedo airport runway surface in the Area 1 location was not properly classified as land pixels by any of the S1SAR inputs, resulting in high commission error compared to the S2MSI imagery, which was able to properly classify the runway.

Conversely, Area 4 surface water maps with S1SAR imagery produced a mean CSI of 0.76 and with S2MSI produced a mean CSI of 0.88 (difference of 0.12), indicating that the quality of the surface water maps for this location were more comparable. Area 4 was characterized by mostly deciduous vegetation, two rivers of different sizes, and gently sloping terrain. Area 2 surface water maps produced mean CSIs of 0.51 and 0.79 (difference of 0.28) from the S1SAR and S2MSI imagery, respectively. The location of Area 2 had the flattest terrain, but some dark crop vegetation in the Area 2A imagery created commission errors for the S1SAR input and the flooded conditions in the Area 2B imagery created both omission and commission errors for the S1SAR and S2MSI imagery inputs. S2MSI imagery is sometimes used for accuracy evaluation of S1SAR surface

water maps (Hu et al., 2020; McCormack et al., 2022; Souza et al., 2022; Ticehurst and Karim, 2023; Tran et al., 2022; Vekaria et al., 2022). From the results of this study, although S1SAR and S2MSI products are of similar spatial resolution, the use of S2MSI-derived surface water maps to validate S1SAR-derived surface water maps is justified, as S2MSI is highly likely to produce a more accurate surface water map than S1SAR.

The trend identified between the local mean incidence angle of the S1SAR imagery and the CSI indicates that if an image with a lower incidence angle is selected to generate a surface water map, the quality of that map may be better than with a higher incidence angle. From literature, the impacts of a larger incidence angle are two-fold and at odds with the goal of increasing map quality. Larger incidence angles result in decreasing backscatter intensities, worsening the classification between water and land, and reduced terrain distortion, improving shoreline detection (European Space Agency, 2007; Kaplan et al., 2021). The impact of backscatter intensity on the CSI was greater than the impact of the terrain correction, and as such, map accuracy decreased with increasing incidence angle. This is of importance as multiple S1SAR images are often available within the same range of dates. If feasible, the image with the lowest local mean incidence angle should be selected for surface water map generation. On the other hand, the Sun zenith angle and S2MSI viewing incidence angle did not trend with the CSI of S2MSI-derived surface water maps, indicating that the angle of the Sun and the angle of viewing may not need to be considered when selecting a S2MSI image to produce a surface water map.

Although S2MSI imagery can produce higher accuracy surface water maps, S1SAR imagery provides many practical advantages over multispectral imagery for a number of applications. Most notably, radar-based imagery is used extensively in flood area mapping and for rapid flood assessment (Hu et al., 2020; Li et al., 2018; Tripathy and Malladi, 2022; Vekaria et al., 2022). This is because floods caused by large rainfall events inherently coincide with cloudy atmospheric conditions, limiting or even completely negating the use of multispectral-based imagery if cloudy conditions are present. Additionally, for near-real-time flood disaster assessment, imagery needs to be available during night hours, highlighting another practical disadvantage of S2MSI imagery. One flooded area was included in this study, Area 2B, illustrated in Figure 4-9.

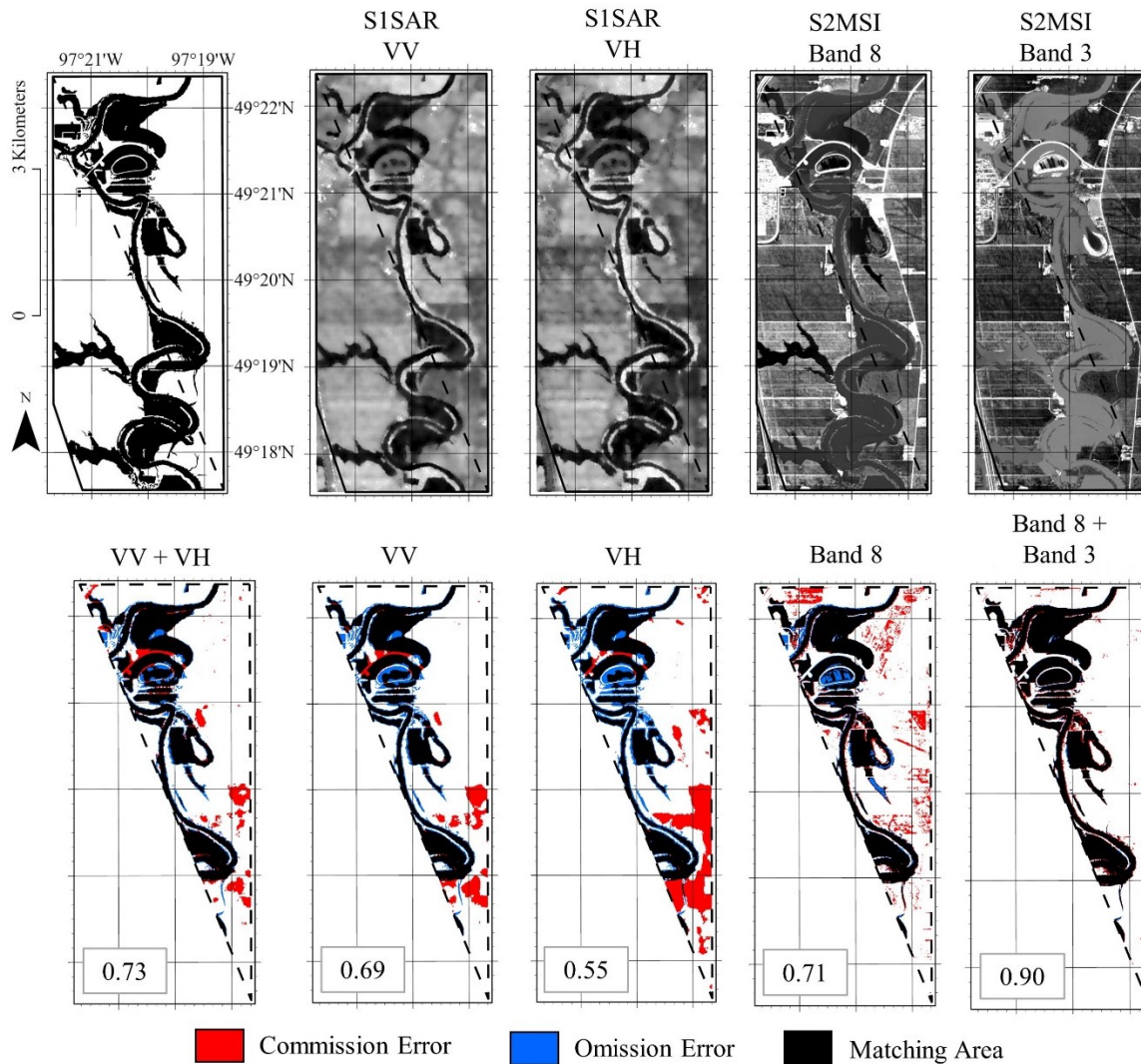


Figure 4-9: Area 2B results using SVM. The CSIs are listed in the lower left corner of the mapping results.

The quality of the surface water maps for the Area 2B image, the only flooded landscape in the dataset, was found to be relatively similar between the S1SAR and S2MSI inputs. The mean CSI for S1SAR was 0.59 and the mean CSI for S2MSI was 0.74. The dual polarization produced a slightly more accurate map than the VV polarization, which is in agreement with existing literature that has theorized that seasonal fluctuations in flooded vegetation can only be captured by dual polarization and not by single polarization (Irwin et al., 2018). The VV polarization was superior to the VH polarization, and dual polarization produced a higher accuracy map compared to the map derived from band 8 of the S2MSI image. However, the addition of band 3 to the classification using S2MSI imagery improved the classification and produced the highest CSI. Thus, although S2MSI imagery produced the most accurate flood extent map, the S1SAR imagery also produced a surface water map of acceptable quality.

Because the inclusion of an additional band of imagery (band 3) was found to significantly improve image classification for multispectral imagery when using machine learning methods, more bands should be included in future comparisons to understand if their effects on image classification accuracy are significant as well. For example, the modified normalized difference water index (MNDWI), normalized difference moisture index (NDMI), and automated water extraction index (AWEI) utilize the blue and short-wave infrared bands (bands 2, 11, and 12, respectively, for S2MSI imagery). Inclusion of these bands of imagery when utilizing machine learning or deep learning methods in image classification may lead to significantly more accurate surface water maps, as shown with the inclusion of band 3 to band 8 in this study.

Previous literature has demonstrated that dual polarization generally produces higher quality surface water maps (Brisco et al., 2008; C. Li et al., 2023; White et al., 2015). However, this study's results have indicated that this is not always the case. The ANOVA analysis *p* value describing the influence of dual polarization and single polarization indicates that the average CSI of the surface water maps produced with dual polarization is not different from the average CSI produced with single polarization. Thus, on average, surface water maps produced by dual polarization images are not superior to those produced with single polarization images, and the differences in surface water map quality are scene and method dependent. Admittedly, due to the small sample size used in this study (eight image locations), this result may not be suitable to describe the population of all other image locations. Other combinations of dual polarizations have been shown to be superior at classifying water than the dual polarizations used in this study (i.e., VV/VH and HH/HV), such as HH/VV and VV/HV (Lee et al., 2001), and as such, further analysis should be performed to understand if HH/VV and VV/HV produce significantly more accurate surface water maps. If so, the availability of such polarization data combinations should be increased. Vekaria et al. (2022) theorized that the VH polarization should be used for flood inundation area monitoring because the VH polarization provides a wide range of backscatter values on the vegetated water surface. Conversely, VV polarization has been theorized to be better for flood extent mapping in other literature (Hu et al., 2020; Li et al., 2018; Twele et al., 2016). This study found that the VV polarization input better represented the flood extent than the VH polarization in the flooded image that was analyzed.

Recent advances have improved flood extent detection using S1SAR imagery beyond what was completed in this study, such as masking using DEMs (Tripathy and Malladi, 2022), dynamic thresholding (Vekaria et al., 2022), change detection (Li et al., 2018; Tripathy and Malladi, 2022), and the combination of ascending and descending scenes (Tripathy and Malladi, 2022). Additionally, the creation of pixel confidence intervals rather than Boolean values (e.g., 0 or false for land, 1 or true for water) and the creation of rapid flood assessment models in cloud-based engines (Tripathy and Malladi,

2022), such as Google Earth Engine, has made S1SAR imagery more useful for flood disaster planning. However, from this study's findings with S1SAR imagery, consideration of the impact of the local incidence angle, terrain correction effects in sloped areas, and the possibility of misclassification caused by certain soil types and vegetation colours impedes confidence in the accuracy of surface water maps produced with S1SAR imagery. Hence, a combination of S1SAR imagery and S2MSI imagery should be used to improve the accuracy of the surface water maps beyond just S1SAR imagery (Manaf et al., 2016; Mansaray et al., 2020; Tang et al., 2022). This study presents a baseline for understanding the multispectral bands and polarizations that should be included in fused imagery. This study illustrates either that the green band of multispectral imagery should be used in addition to the NIR band or that a spectral index method that uses at least both the green and NIR bands of imagery should be used. These bands or indexed images should be employed when fusing with S1SAR imagery. Optical and radar fused imagery is useful in a variety of disciplines apart from flood extent detection, such as object detection in autonomous driving on water surfaces (Yao et al., 2024). Additionally, the fusion of S1SAR imagery with the newly developed GLH-Water dataset, which is proposed to provide high-resolution surface water maps globally, may be able to provide improved water change detection capabilities for the rapid mapping of flood extents (Y. Li et al., 2023).

For areas in which seasonal runoff is dominated by snow/ice melt, differentiation of liquid water from ice and snow using remotely sensed data is particularly important, as flood season often coincides with melting and ice-break up activities. To track ice-jam locations and facilitate flood disaster assessment and planning, it is important to know which satellite imagery product is most likely to best distinguish liquid water from ice and snow. Previous literature has indicated that ice and vegetated areas are able to be distinguished from open water with dual polarization data and are often misclassified with single polarization data (Irwin et al., 2018). Area 2B in this analysis included multiple areas of ice, one of which is illustrated in Figure 4-10.

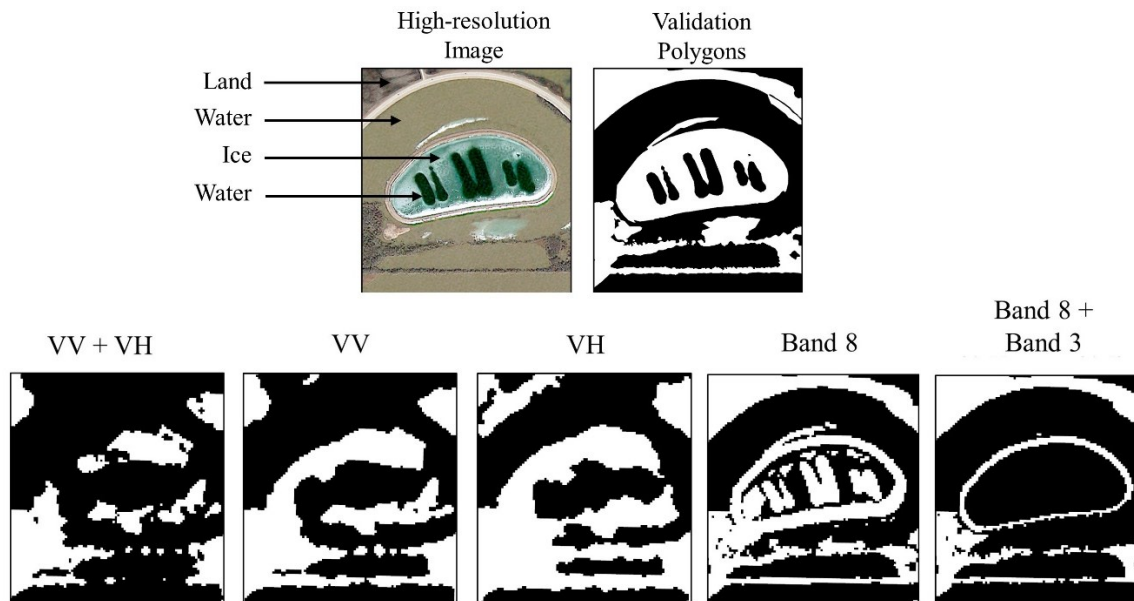


Figure 4-10: Surface water mapping results of the ice located in the Area 2B image using SVM technique.

In Figure 4-10, it is demonstrated that, overall, the VH polarization best discerns the ice from the liquid water, and the S2MSI inputs either completely classify the ice/water area as water (band 8 + band 3) or the classified areas are swapped, creating both omission and commission errors (band 8). Both single polarizations perform better at distinguishing ice from water compared to dual polarization, which is in contrast with the existing literature. The summary of this study's findings is presented in Table 4-4. The findings derived using all study areas are separated from the findings generated from the characteristics from study Area 2B (flooded areas and ice areas), as the conclusions derived from the eight image areas combined are stronger than that of the single Area 2B image area. The results regarding which imagery input is best for flooded and icy/snowy image features could be made stronger with the analysis of multiple images with such features. Thus, more research should be conducted into which polarization of radar-based imagery is better at properly discerning ice and snow from water, particularly in flooded landscapes.

Table 4-4: Summary of findings

Objective	Finding
Overall, across all study areas	
S1SAR vs. S2MSI	S2MSI statistically superior
Single vs. dual polarization	Neither statistically superior
Like vs cross-polarization	Neither statistically superior
NIR vs. green + NIR	Green + NIR statistically superior
KNN vs. MLC vs. RT vs. SVM	SVM superior (not statistically tested)
For Area 2B	

Best input for mapping flooded area	S2MSI superior; for S1SAR, dual superior to single polarization
Best input for mapping ice area	Cross-polarization superior across S1SAR and S2MSI

4.6 Conclusions and Recommendations

In this study, surface water maps were derived at four study locations during two distinct flow conditions at each location. Surface water maps were derived from S1SAR and S2MSI imagery using four machine learning methods. In addition, the polarizations of the radar imagery and the bands of the multispectral imagery were varied. Altogether, 160 surface water maps were developed providing a basis for statistical analyses. The large scope of this analysis is rare in remote sensing research, and it allowed for ANOVA testing to determine whether the difference in accuracy derived from the various imagery products was significant. The comparison metric used was the CSI, which is used commonly in flood model extent validation. The high-resolution validation imagery was selected to be as temporally close as possible to the S1SAR and S2MSI imagery capture dates.

The surface water maps derived from S2MSI imagery were found to be of significantly higher accuracy than surface water maps derived from S1SAR imagery ($p < 0.001$). Thus, if possible, S2MSI imagery should be used for surface water mapping. However, the lower availability of cloud-free S2MSI images during storms provides a practical limitation of the use of S2MSI imagery compared to S1SAR imagery, which is more useful for flood extent mapping and rapid analysis. This study justifies the use of S2MSI-derived surface water maps to validate surface water maps generated from S1SAR imagery (Hu et al., 2020; McCormack et al., 2022; Souza et al., 2022; Ticehurst and Karim, 2023; Tran et al., 2022; Vekaria et al., 2022), despite the similarity in the products' spatial resolution.

Upon comparing the S1SAR polarizations and S2MSI bands for surface water detection, findings that either bolster or contradict existing literature were discovered. Between like- and cross-polarization, no difference in the mean accuracy of the surface water maps was established ($p = 0.973$). A similar result was found between dual and single polarization ($p = 0.511$). Both of these findings are in contrast with the existing literature (Abbasi et al., 2023; Bangira et al., 2019; Brisco et al., 2008; Haris et al., 2021; C. Li et al., 2023; Souza et al., 2022; Twele et al., 2016; White et al., 2015). Rather, this study has found that the difference in accuracy between the polarizations is location/image and method dependent. However, only VV, VH, and VV/VH polarizations were tested in this study and a significant difference in accuracy may exist for the dual polarizations HH/VV or VV/HV (Lee et al., 2001). Thus, future work exploring these additional polarization options would provide a valuable contribution to land-water image

classification research. Conversely, the addition of the green band (band 3) of multispectral imagery was found to significantly improve ($p = 0.010$) the mean accuracy of water surface maps beyond the use of just the NIR band (band 8). Thus, when employing traditional machine learning techniques, band 3 should be used in addition to band 8.

In the flooded study location, the dual polarization produced the highest accuracy surface water map for S1SAR imagery, in agreement with existing literature (Irwin et al., 2018). Additionally, the like-polarization performed better than cross-polarization for the flooded image, which is also in agreement with existing literature (Abbasi et al., 2023; Brisco et al., 2008; Hu et al., 2020; Li et al., 2018; Twele et al., 2016). Thus, dual polarization should be used for flood inundation extent detection, if available, and like-polarization should be used otherwise. With ice present, the cross-polarization was observed to best differentiate ice from liquid water when compared to dual and like-polarization for S1SAR imagery and when compared to band 3 and band 8 for S2MSI imagery.

Chapter 5. Optimization of Surface Water Mapping Methods

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Ferguson, S., Rennie, C.D., Cousineau, J., Nistor, I., 2024. Identification of the best method for detecting surface water in Sentinel-2 multispectral satellite imagery. *Remote Sens. Appl. Soc. Environ.* 101367. <https://doi.org/10.1016/j.rsase.2024>.

Abstract:

Surface water maps are useful in a variety of disciplines from climate change analysis to water resource management. Multispectral satellite imagery can be used to derive such surface water maps using a variety of image processing methods. The medium resolution Sentinel-2 multispectral satellite imagery catalogue is currently used extensively for surface water mapping. The quality and accuracy of these maps produced from Sentinel-2 imagery can vary greatly depending on the method applied to classify the image pixels into land or water. Thus far, there has not been a consensus on which method produces the highest accuracy surface water maps, warranting a direct comparison to assess these methods in a wide range of geographic settings. Here we show that among some of the most commonly applied surface water mapping methods (NDWI, MNDWI, AWEI_SH, AWEI_NSH, AWEI_BOTH, SVM, RT, MLC, and KNN) that no single method produced the most accurate maps across the four locations studied, but AWEI_NSH performed the best overall across the four locations, and SVM was the best performing machine learning technique. Rather, each method's performance was shown to depend on the objects present in the image (e.g., built-up, shadows, vegetated shorelines, narrow waterbodies, etc.) and how successfully the method was able to classify those objects properly. This is in-line with current understanding of spectral index methods' performance, and we provide recommendations to aid remote sensing data users in choosing a suitable method based on their image's characteristics. Using these recommendations, we hope that the quality of surface water maps derived from multispectral satellite imagery will be improved for all disciplines that utilize such data by allowing users to choose the method that is best fit to the application.

Keywords: Surface water mapping; remote sensing classification; AWEI; NDWI; Sentinel-2 multispectral satellite imagery; earth observation

5.1 Introduction

Remotely sensed satellite imagery is a valuable source of data to understand the impact of humans on the environment and the impact of the environmental processes on

humans at a moment or over a period of time. Satellite imagery can be used to investigate a variety of anthropogenic activities and their consequences as well as environmental phenomena, including deforestation, agricultural intensification, urbanization, flooding, droughts, natural fires, and volcanic activity. Remotely sensed satellite data are generally processed via classification methods into Land Cover and Land Use (LCLU) data and are a valuable resource to produce large Earth Observation (EO) datasets and Satellite Image Time Series (E. D. Chaves et al., 2020). A subcategory of LCLU data are remotely sensed satellite data that are classified into just two categories: land and water pixels. This is done to closely analyze the relationship between humans and the Earth's surface water. Surface water mapping or land-water image classification (LWIC) of satellite imagery is a popular research topic and has included detection of dam surface water (Yilmaz et al., 2023), floods (Ireland et al., 2015), rice crops (Boschetti et al., 2014), coastal lagoons (Senel et al., 2020), wetlands (Pena-Regueiro et al., 2020), and lakes (Roach et al., 2012; Thati et al., 2021). Additionally, land-water classified satellite data have been used to track changes in surface water extent (Kseňak et al., 2022) or shoreline deviation (Alcaras et al., 2022; Manaf et al., 2016) for climate change purposes. However, successful classification of remotely sensed satellite data into land and water pixels is a process that can be impacted by numerous factors (Khatami et al., 2016), and many methods to perform LWIC exist with varying levels of accuracy. Thus, it is the goal of this study to test commonly used LWIC methods to identify which method performs best overall and to identify what characteristics or objects within the image impact the quality of the surface water maps produced by each method.

Most applications of remote sensing satellite data classification have been developed for moderate spatial resolution instruments (e.g., the Moderate Resolution Imaging Spectroradiometer or MODIS at 250 x 250 m) (Bolton et al., 2020; E. D. Chaves et al., 2020). More recently, there has been heavy emphasis on utilizing the medium-resolution (e.g., 30 x 30 m) Landsat image series, specifically Landsat-5 Thematic Mapper (L5TM), Landsat-7 Enhanced Thematic Mapper (L7ETM), and Landsat-8 Operational Land Imager (L8OLI), for EO applications, as medium-resolution data are more suitable to detect changes in human-environment systems at regional scales (Chen et al., 2015; Huang et al., 2020). The Landsat resources cover a timespan from 1984 to present and have a repeat cycle of 16 days. In contrast, similar products from the Sentinel-2 MultiSpectral Instrument (S2MSI) cover a timespan from 2015 to present and have a repeat cycle of 5 days. This shorter time span of available imagery may explain why, comparatively, less image classification research and application has been conducted using S2MSI, despite the fact that several S2MSI bands have a finer spatial resolution than the Landsat resources. For example, S2MSI bands 2, 3, 4, and 8 have a spatial resolution of 10m compared to L8OLI which has a spatial resolution of 30m (Department of the Interior and U.S. Geological Survey, 2021; ESA, 2023).

LWIC relies on the principle that water pixels and non-water pixels will have different reflectance values. For multispectral imagery (L8OLI and S2MSI), each band of the imagery represents a different wavelength of light (see Table 5-2 for S2MSI bands and comparable L8OLI bands), and water more readily absorbs certain wavelengths of light than others. In particular, light in the near infrared (NIR) and shortwave infrared (SWIR) wavelengths are more readily absorbed by water than land. This difference in absorption can be enhanced through spectral indexes or classical machine learning methods, to name a few. The simplest LWIC method is Density Slicing where a single band of the imagery is used, and a pixel value threshold is selected to classify image pixels into the land category or the water category (Bijeesh and Narasimhamurthy, 2020). Multiple slices or intervals can be applied to classify the image pixels into categories corresponding to the likelihood of the pixel representing water or land (Bijeesh and Narasimhamurthy, 2020). Instead of using a single band of imagery, a spectral index can be used to make use of multiple bands of imagery to better differentiate between land and water. Common spectral index-based LWIC methods include the Water Ratio Index (WRI) (Shen and Li, 2010), the Normalized Difference Water Index (NDWI) (McFeeters, 1996), the Normalized Difference Vegetation Index (NDVI) (Goward et al., 1991), the Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and the Automated Water Extraction Index Shadow (AWEI_SH) and No Shadow (AWEI_NSH) (Feyisa et al., 2014). Spectral index-based methods can only be applied to multispectral imagery. The general categories of common classical machine learning based methods include Support Vector Machine (SVM) (Cortes and Vapnik, 1995), Random Trees (RT) or Random Forest (RF) (Breiman, 2001), Maximum Likelihood Classifier (MLC), K-nearest Neighbour (KNN) (Cover and Hart, 1967), K-means Clustering Algorithm (Hartigan and Wong, 1979), Artificial Neural Network (ANN) (Schalkoff, 1997), and Iterative Self-Organizing Data Analysis Technique (ISODATA) (Ball and Hall, 1965). Many more LWIC methods exist beyond those stated (Bijeesh and Narasimhamurthy, 2020), and countless more exist when considering the combination of spectral index-based methods and machine learning based methods (e.g., applying machine learning methods to an image that has had a spectral index applied to it). Studies that have compared the success of these methods at LWIC have produced diverging results. Many studies have found that NDWI produced superior results in their study location compared to other indexing methods (Alcaras et al., 2022; Aroma and Raimond, 2021; Doña et al., 2016; Mukherjee and Samuel, 2016; Pena-Regueiro et al., 2020; Zhang et al., 2022), while some studies specify NDWI only performed best under specific conditions (e.g., it performs best in high mountains (Hafiza Wajiha Khalid et al., 2021) or shallow waters (Yilmaz et al., 2023)) or even that NDWI performed poorly overall compared to other methods (Gudelj et al., 2018; Ireland et al., 2015; Senel et al., 2020). Other studies have demonstrated that AWEI ((Feyisa et al., 2014; Senel et al., 2020)), SVM ((Feizizadeh et al., 2023; Li et al., 2022; Manaf et al., 2016)), or RF ((Gudelj et al., 2018; Otukey and Blaschke, 2010; Singh and

Pandey, 2021; Yilmaz et al., 2023)) produced the most accurate LWIC data in their study location. Additional observations include that MNDWI performed best in clear water (Sun et al., 2012), that MLC performed best in scene with built up environment (i.e., urban infrastructure) (Sun et al., 2012), that AWEI, SVM, and RF performed best in hilly, flat regions (Hafiza Wajiha Khalid et al., 2021), and that ISODATA was the best performing method in the study area (Thati et al., 2021). These examples illustrate the range and inconsistency of findings from previous research focused on assessing suitability of LWIC methods. These inconsistencies may be linked to site- or condition-specific factors that influence the performance and suitability of various LWIC methods.

Some research gaps are present that have not been fully addressed by existing literature comparing the performance of various LWIC methods. First, it is uncommon for the LWIC methods to be compared in multiple locations with different objects and characteristics present in the imagery. Therefore, sensitivity to various site- and condition-specific factors such as vegetation cover, soil types, built-up, and the presence of shadows is not well understood. In addition, the spectral index-based methods that have been evaluated in past studies were often applied using a single threshold, often selected using fundamental thresholding algorithms such as Otsu's method. In some studies, a threshold of zero was chosen (Sun et al., 2012; Wei et al., 2020), and, rather than testing the success of the method at detecting water, this tested the stability of the spectral based-index's threshold around the number zero. Most often, the Otsu global threshold selection algorithm was applied (Ireland et al., 2015; Kseňak et al., 2022; Li et al., 2022; Thati et al., 2021), or it was not explicitly stated how thresholding was conducted. Therefore, the degree to which individual LWIC methods were optimized prior to comparison with other LWIC methods is often unclear or not fully considered in past research. Threshold selection sensitivity across multiple spectral indices and across multiple image locations, in the interest of optimizing the accuracy of classified land and water pixels, has been a rarely studied subject. However, the comparison of the performance of various automated thresholding algorithms has been explored thoroughly in past research at a single waterbody location (Karaman, 2021; Sekertekin, 2021). This research found that the minimum thresholding method produced the most accurate classification at their study site (Karaman, 2021; Sekertekin, 2021), although Otsu's method is generally the most widely applied automated threshold selection algorithm. Additionally, error analysis of LWIC methods has sometimes been performed with medium resolution imagery (Boschetti et al., 2014; Sekertekin, 2021; Wei et al., 2020), so small differences in classification results caused by the different LWIC methods compared could not be observed at a fine resolution. Finally, image classification results have often been assessed by evaluating the classification accuracy at randomly selected points in the image (i.e., the kappa coefficient approach) (Doña et al., 2016; Hafiza Wajiha Khalid et al., 2021; Mansaray et al., 2020; Pena-Regueiro et al., 2020; Yilmaz et al., 2023; Zhang et al., 2022) or in-situ measured shoreline points (Karaman, 2021). However, these

approaches can limit the observations that are able to be made regarding the image characteristics that cause misclassifications (e.g., wet sand, certain types of infrastructure or vegetation, etc.) compared to when performing validation using high resolution imagery.

Due to these aforementioned research gaps, this study attempts to:

- Determine if there is an ideal method to perform LWIC of satellite imagery across multiple locations and to
- Identify the characteristics of images that can cause misclassifications among these commonly applied LWIC methods.

This is the first study that this degree of comparison was performed for surface water mapping, as nine methods were compared across four diverse images with varied image characteristics across Canada. To ensure fair comparison, each image was prepared to the same level of pre-processing (Section 5.3.1), and each method was optimized by testing the stability of the thresholds for spectral index-based classifiers (Section 5.3.2.3). The optimized thresholds were also tested against the thresholds selected via Otsu's method, to understand the ability of Otsu's method at selecting a suitable threshold. Additionally, the effects of resampling the 20 m multispectral bands of S2MSI imagery to 10 m were evaluated. The success of each method was tested using two baselines: the critical success index (CSI, Section 5.3.3.1) and the root mean squared error of river widths (Section 5.3.3.2). It is hoped that this work will be used to guide individuals to use the LWIC methods and optimization techniques best suited for their image of interest in order to create high quality surface water maps.

5.2 Study Location and Data Acquisition

The S2MSI imagery evaluated in this paper was open-source and downloaded through Copernicus Open Access Hub. S2MSI imagery was chosen for analysis in this paper as it is used extensively in surface water mapping applications. It provides a higher resolution than the Landsat series, although the Landsat series has greater temporal coverage. Because of the similarities between these two multispectral imagery catalogues (see Table 5-2 for similar band wavelengths between the two products), the findings in this paper are expected to also be useful for the Landsat series. The S2MSI imagery is available in two levels of processing: top of atmosphere (TOA) in Level 1C and bottom of atmosphere (BOA) in Level 2A. Level 2A products are only available for dates 2019 to present and Level 1C is available for 2015 to present.

Four locations in Canada were chosen for analysis based on the following considerations in an attempt to diversify the image characteristics as much as possible: soil, vegetation, built-up, depth and turbidity of water, high albedo surfaces, presence of shadow, presence of snow, and seasonality of imagery. The four locations are shown in

Figure 5-1 and are the Red River (RedR) near Morris, Manitoba, in UTM zone 14N, the Sylvia Grinnell River (SGR) near Iqaluit, Nunavut, in UTM Zone 19N, the Rivière-Rouge (RougeR) and Ottawa River near L'Original, Ontario, in UTM Zone 18N, and the Fraser River (FR) near Xaxli'p First Nation, British Columbia, in UTM Zone 10N. The image for the RedR location was taken during a high flow event (50th percentile flow is 66), the image for the SGR location was taken during a high flow event (50th percentile flow is 58), the image for the RougeR location was taken during a mid-flow event (50th percentile flow is 71), and the image for the FR location was taken during a high flow event (50th percentile flow is 1010). Because all study locations were selected within Canada, there may be a lack of generalizability to the study. However, the RougeR and FR locations are situated approximately 3500km apart in the longitudinal direction, and the RougeR and SGR locations are situated approximately 2100km apart in the latitudinal direction. Thus, the breadth of image landcover, vegetation, and climates are varied between the four image areas. Table A1 in the supplementary material lists all landcover classes included in the image areas. Additionally, the effects of seasonal variation (e.g., additional hydrological conditions at each location) were not explored in this work as a single hydrological condition was analyzed for each image area.

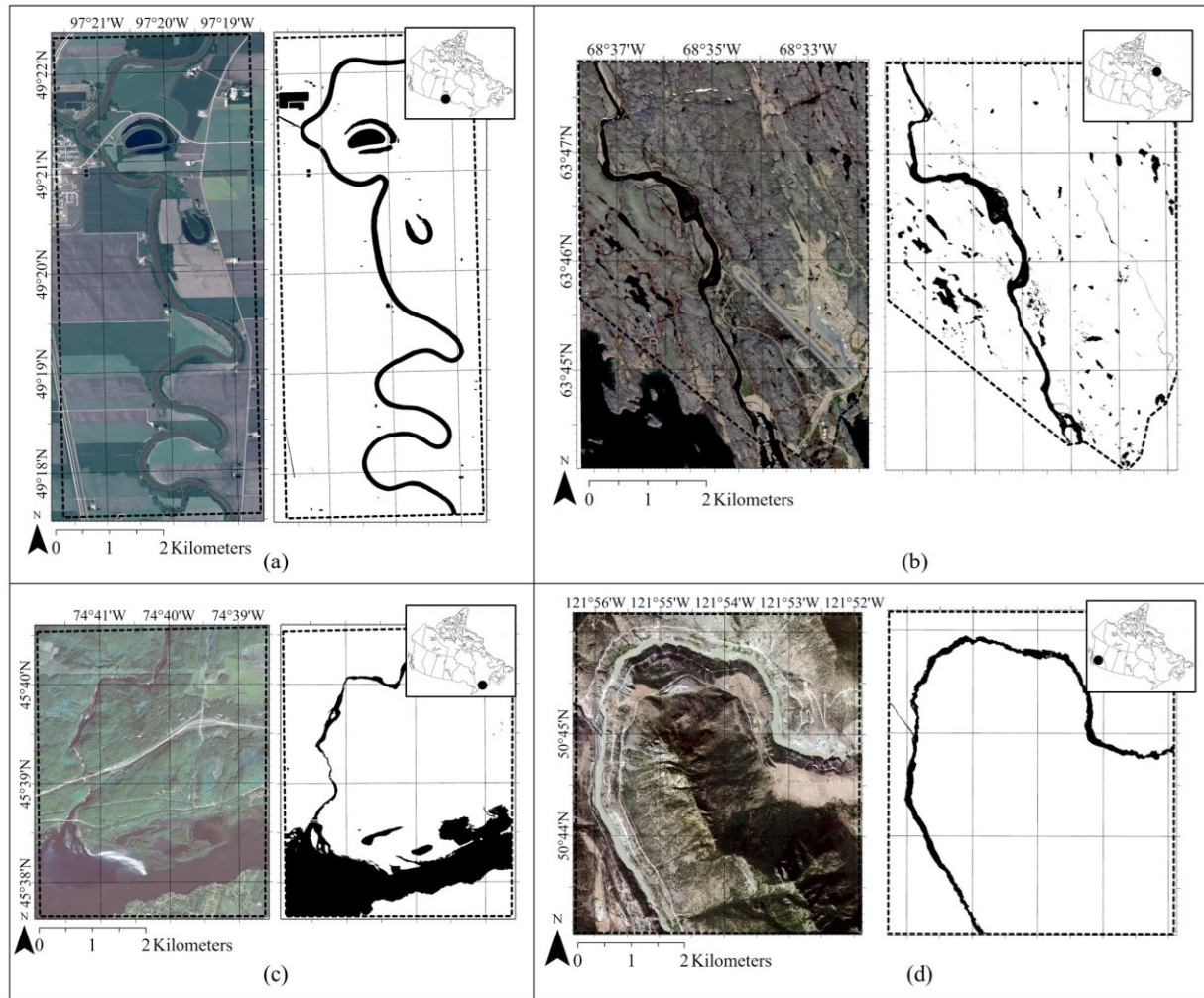


Figure 5-1: Study locations and water polygons derived from high resolution imagery for validation purposes: (a) Red River (RedR), (b) Sylvia Grinnell River (SGR), (c) Rivière-Rouge (RougeR), and (d) Fraser River (FR).

The Landcover of Canada dataset (Canada Centre for Remote Sensing; Natural Resources Canada; Government of Canada, 2015) (Table A1 in supplementary material) was used to ensure the locations were varied enough to draw conclusions about the influence of image characteristics on the success of LWIC. Snow and ice are included in the SGR image as the river is located in the Arctic, and shadows are present in the FR image as the river is located in a canyon. Snow/ice and shadows are often difficult to discern from liquid water in satellite imagery. Some other characteristics that were captured in the various locations were: different turbidity in waterbodies (all four locations), many small bodies of water (SGR), uniform river size (RedR), narrow river size and rapids (RougeR and SGR), built-up (all four locations), and river confluences (RedR, RougeR, FR). Table A1 summarizes the landcover classes that are represented in each of the four locations. Although detailed quantitative data related to the turbidity and water

quality (e.g., salinity, sediment concentration, chl-a) for each of the waterbodies in the four locations was not available, quantitative observations and generalized qualitative data were available from personal experience, field data collection at these locations (Kirby et al., 2023b; Venditti et al., 2014), and historical measurements from the Water Survey of Canada (Government of Canada, 2024). The Red River in the RedR image location has high turbidity and low salinity. The average suspended sediment concentration across 1956 to 1961 in the Red River was 303 mg/L. The Sylvia Grinnell River in the SGR image location has very low turbidity (nearly clear) and low salinity. Suspended sediment data was not available for the Sylvia Grinnell River. The Rivière-Rouge and Ottawa River in the RougeR image location have medium turbidity and low salinity. The average suspended sediment concentration across 1977 to 1979 in the Ottawa River was 37 mg/L. The Fraser River in the FR image location has high turbidity and low salinity. The average suspended sediment concentration across 1965 to 1979 in the Fraser River was 125mg/L.

To perform comparison analysis, validation data were generated from high resolution imagery (shown in Figure 5-1). Water polygons were manually drawn from the high-resolution images, and it is assumed that there are negligible errors associated with these water extents. The S2MSI images were chosen to be as close to the high-resolution imagery date as possible with cloud-free conditions. The dates of all the images are presented in Table 5-1, as well as the high-resolution imagery sources and resolutions. Level 2A S2MSI imagery was used for the RedR, RougeR, and FR sites. For the SGR site, only Level 1C S2MSI imagery was available for the date of interest.

Table 5-1: Study locations and characteristics

Location	Area [km ²]	Date of high-resolution image	Source and resolution of high-resolution image	Date of S2MSI image	River flow rate* [m ³ /s]	Mean river width [m]	Surficial Geology **
Red River (RedR)	33	2019/06/30	PLÉIADES 1 50cm	2019/06/30	171	80	Silt and clay, locally containing stone
Sylvia Grinnell River (SGR)	39	2018/07/21	WorldView-2 50cm	2018/07/21	178	120	Till blanket; diamicton; thick and continuous
Rivière-Rouge (RougeR)	25	2019/09/29	TripleSat 80cm	2019/09/21	61	50	Sand and gravel; variable thickness
Fraser River (FR)	30	2020/09/08	KOMPSAT-3 70cm	2020/09/07	2110	75	Colluvial deposits, undifferentiated; blocks, rubble with sand and silt with minor clay

* River flow information from Water Survey of Canada (Government of Canada, 2023)

** Surficial Geology from the Gridded Soil Landscapes of Canada (Agriculture and Agri-Food Canada; Science and Technology Branch; Government of Canada, 2016)

5.3 Methods

5.3.1 Image Preparation

No pre-processing was required for the Level 2A S2MSI images which are already corrected to BOA reflectance. The Level 1C S2MSI image for the SGR site was converted from TOA to BOA reflectance using the Sen2Cor tool (Main-Knorn et al., 2017) in the SeNtinel Application Platform (SNAP). The Sen2cor algorithm begins by applying a series of threshold tests to identify clouds, snow, and other image features. The algorithm then uses these features' reflective properties to calculate atmospheric and surface parameters for future processing steps. Then atmospheric correction is completed based on aerosol and ozone values related to the image's geographic location. The pre-processing and main processing steps for the S2MSI images are shown in Figure 5-2.

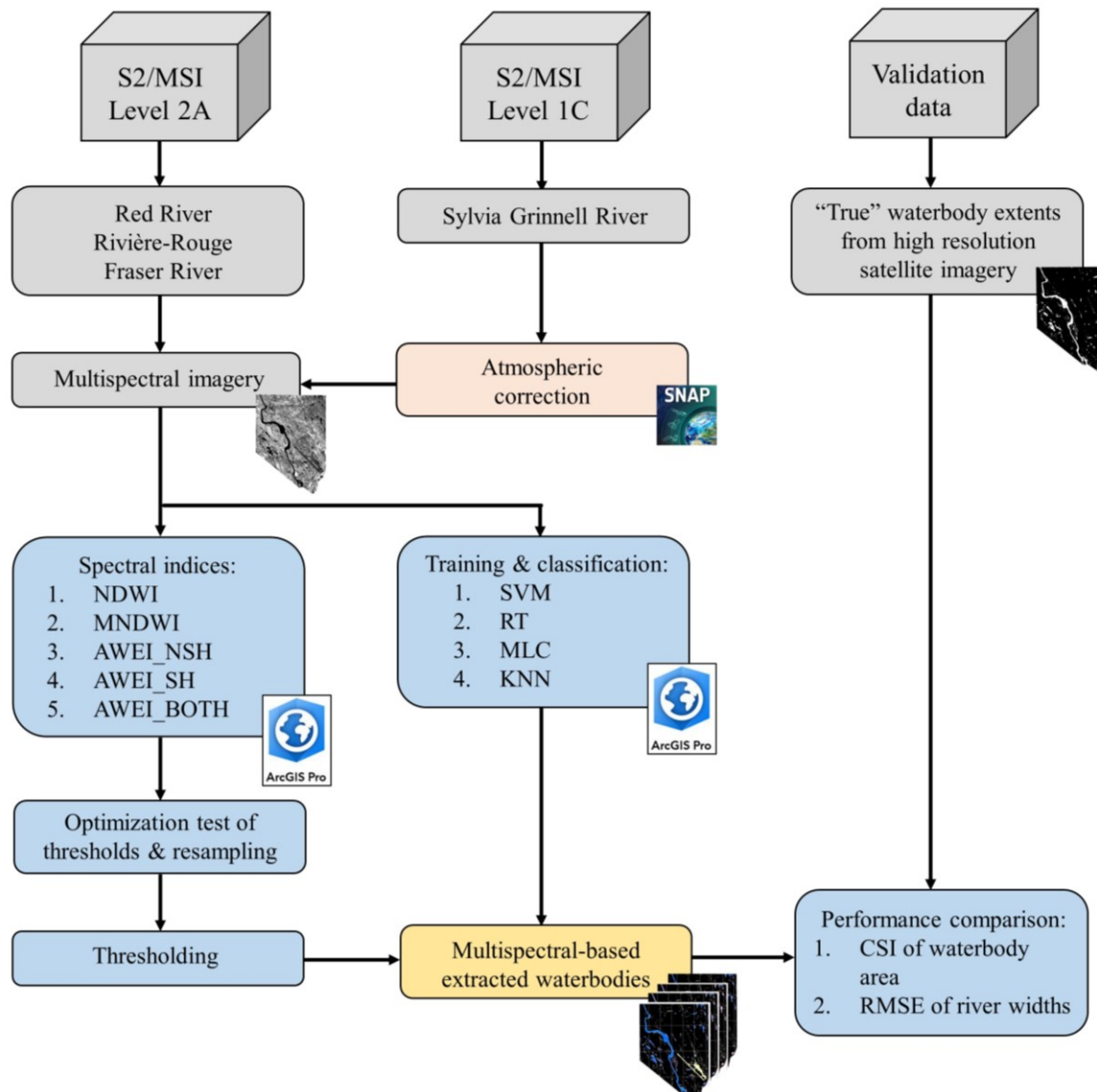


Figure 5-2: Methodology framework. Grey boxes represent processing inputs, yellow boxes represent intermediate processing products, orange boxes represent image pre-processing steps, and blue boxes represent main processing steps.

5.3.2 Image Processing and Optimized Thresholding

5.3.2.1 Spectral Indices

For multispectral imagery, LWIC was conducted using both spectral index-based and classical machine learning-based methods, as illustrated in Figure 5-2. The spectral indices applied were NDWI, MNDWI, AWEI_NSH, and AWEI_SH. The equations for these indices are shown below where the subscripts of each wavelength correspond to the bands presented in Table 5-2. These indices are also applicable for use with bands of similar wavelengths for Landsat 8 imagery, and thus it is likely that this study's findings

are also applicable to the Landsat imagery catalogue. The processing was completed using ArcGIS Pro Version 3.03.

$$[5-1] NDWI = \frac{\rho_{green} - \rho_{NIR}}{\rho_{green} + \rho_{NIR}}$$

$$[5-2] MNDWI = \frac{\rho_{green} - \rho_{SWIR1}}{\rho_{green} + \rho_{SWIR1}}$$

$$[5-3] AWEI_NSH = 4 \times (\rho_{green} - \rho_{SWIR1}) - (0.25 \times \rho_{NIR} + 2.75 \times \rho_{SWIR2})$$

$$[5-4] AWEI_SH = \rho_{green} + 2.5 \times \rho_{blue} - 1.5 \times (\rho_{NIR} + \rho_{SWIR1}) - 0.25 \times \rho_{SWIR2}$$

where ρ_{blue} is the reflectance of the blue band (band 2 in S2MSI), ρ_{green} is reflectance of the green band (band 3 in S2MSI), ρ_{NIR} is the reflectance of the NIR band (band 8 in S2MSI), ρ_{SWIR1} is the reflectance of the first SWIR band (band 11 in S2MSI), and ρ_{SWIR2} is the reflectance of the second SWIR band (band 12 in S2MSI). An additional parameter, AWEI_BOTH, was generated by merging the waterbody areas detected by both AWEI_NSH and AWEI_SH.

Table 5-2: S2MSI imagery resolutions, wavelengths, and comparable L8/OLI bands (Department of the Interior and U.S. Geological Survey, 2021; ESA, 2023)

Band	Resolution [m]	Central wavelength [μm]	Description	L8/OLI equivalent band (central wavelength)
1	60	0.443	Coastal & aerosol	-
2	10	0.490	Blue	1 (0.482)
3	10	0.560	Green	2 (0.561)
4	10	0.665	Red	3 (0.656)
5	20	0.705	Visible and NIR	-
6	20	0.740	Visible and NIR	-
7	20	0.783	Visible and NIR	-
8	10	0.842	Visible and NIR	4 (0.865)
8a	20	0.865	Visible and NIR	-
9	60	0.940	SWIR	-
10	60	1.375	SWIR	-
11	20	1.610	SWIR	5 (1.609)
12	20	2.190	SWIR	7 (2.201)

5.3.2.2 Resampling

As shown in Table 5-2, bands 2, 3, 4, and 8 (blue, green, red, NIR) have a pixel resolution of 10m, but the two SWIR bands (11 and 12) have pixel resolution 20m. The indices MNDWI, AWEI_NSH, and AWEI_SH include one or more SWIR band. Thus, the impact of resampling the SWIR band from 20m to 10m on the LWIC results was also studied for each location. The resampling algorithm used in this study was the cubic resampling algorithm. It resamples by performing a cubic convolution, and the updated

cell value is calculated by fitting a curve through the 16 nearest cell centres. This approach was suitable as the raster data used in the study was continuous.

5.3.2.3 Thresholding Procedure

For each image and each spectral index-based classifier, the threshold selected to distinguish water from land was optimized manually to: (1) be able to compare the results of each method while optimized in order to diminish the influence of the threshold selection on the success of the methods and (2) to compare against the threshold selected by Otsu's method. The methodology of the manual threshold adjustment is present in Figure 5-3.

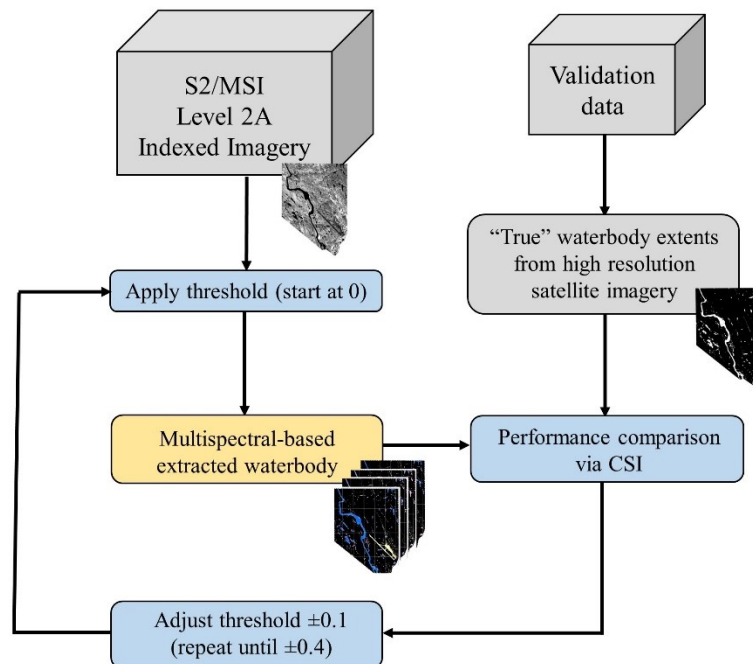


Figure 5-3: Methodology of manual threshold adjustment procedure. Grey boxes represent processing inputs, yellow boxes represent intermediate processing products, and blue boxes represent main processing steps.

By comparing the manually determined optimized threshold against the Otsu threshold, the reliability of Otsu's method was tested. Otsu's method of determining an optimal threshold consists of minimizing the intra-class variance between the background and foreground classes by utilizing the zeroth and the first order cumulative moments of the grey-level histogram (Otsu, 1979). To manually determine the optimal threshold for NDWI, MNDWI, AWEI_SH, AWEI_NSH, and AWEI_BOTH, a sensitivity test for the optimal threshold was performed by varying the threshold by 0.1 intervals from +0.4 to -0.4. As such, the following thresholds were tested for each spectral index: 0.4, 0.3, 0.2, 0.1, 0, -0.1, -0.2, -0.3, and -0.4. The success of the resulting classified image produced

by each threshold was then tested using the CSI (see Equation 5-5). The threshold with the highest CSI was the optimized threshold and was used in future comparisons.

5.3.2.4 *Machine Learning Algorithms*

The classical machine learning-based LWIC methods compared in this paper are SVM, RT (or RF), MLC, and KNN. The classical machine learning tools were tested using the default user settings within the ArcGIS Pro environment, as described herein. This enabled comparison of machine learning tools that are readily available for processing multiple images over large domains to identify waterbodies. SVM is based on statistical learning theory (Smola and Schölkopf, 2004) which is used to locate boundaries of different classes. The SVM algorithm applied in this study used nonlinear radial basis function with a 2S grid and optimal parameter pairs (C, gamma) for the kernels used (Li et al., 2022). Additionally, it does not assume that the samples follow a normal distribution. The default value of 1000 training samples per class was used for the SVM technique. RT (or RF) first uses training samples to generate a discriminant function and then builds branches according to differing values. The process is repeated between lower nodes and branches in each subset until the classification tree is formed (Li et al., 2022). The random forest algorithm developed by Leo Breiman and Adele Cutler (Breiman, 2001) was used, and the function is resistant to overfitting. Default numbers of 50 maximum trees, 30 maximum tree depth, and 1000 samples per class were used for the RT function. MLC is a parametric classifier based on the Gaussian probability density function model, which essentially calculates the possibility that each pixel can be included into a particular class (Paola and Schowengerdt, 1995). KNN classification, the input for the training is the “k” closest examples in the samples. The training samples are assigned to their respective classes via the training process (Cover and Hart, 1967). Default values of 1 neighbour and 1000 samples per class were used for the KNN technique.

For each study location, the high-resolution imagery was divided into two halves. One half was used to train each machine learning method. The remaining half was used to evaluate the results of the LWIC. Therefore, the training/validation split for each location was 50/50. The spatial split of each of the four high-resolution images between training and validation was performed in an attempt to include the unique image characteristics (e.g., built up, high albedo surfaces, shadows, snow/ice, etc.) in both the training and validation samples.

5.3.3 Accuracy Analysis

5.3.3.1 *Comparison on the Basis of Waterbody Area*

Error analysis was performed by comparing the predicted waterbody area to the actual waterbody area (i.e., the waterbody area manually delineated from high-resolution satellite imagery), rather than comparison based on randomly selected points. The advantage of this comparison over randomly selected points is that many observations across the entire image’s extent can be made regarding the characteristics in the images

that cause misclassification, rather than observations that could be made only at the locations of the randomly selected points. Additionally, this method ensures that small differences between the results of the LWIC methods are captured. Error analysis was performed using the CSI, shown below:

$$[5-5] \text{ CSI} = \frac{X}{X+Y+Z}$$

where X are the correct predictions made by the model (in km²), or hits, Y are the overpredictions by the model (in km²), or false alarms, and Z are the underpredictions by the model (in km²), or misses (Lim and Brandt, 2019). The CSI is commonly used as a verification statistic for flood modelling accuracy (Sreekumar et al., 2022). Supplementary to these definitions for flood modelling, X , Y , and Z will be defined as the matching area (MA), the commission error (CE), and the omission error (OE) for the purposes of satellite imagery classification herein. In short, OE is where water was predicted at locations where there is no water in reality, and CE is where land was predicted and where there was no land in reality.

5.3.3.2 Comparison on the Basis of Waterbody Boundary

In addition to evaluating the success of LWIC methods at detecting the correct waterbody area, analysis of the widths of the rivers extracted was performed to evaluate the success of the LWIC methods at detecting the waterbody boundaries. This method has been used in floodplain modelling accuracy assessment as well (Lim and Brandt, 2019; Sreekumar et al., 2022). River centerlines were generated using the true river extents and any flow split (caused by islands, sandbars, etc.) had an associated centerline. Perpendicular transects were generated along the river centerlines at 100m intervals. The transects were clipped to the true waterbody extent for the measured river width. The transects were also clipped to the extracted waterbody extent for the estimated river width. The two widths (measured and estimated) were compared using root mean squared error (RMSE) and mean absolute error (MAE), shown below:

$$[5-6] \text{ RMSE} = \sqrt{\frac{\sum_{i=1}^N (w_i - \hat{w}_i)^2}{N}}$$

$$[5-7] \text{ MAE} = \frac{\sum_{i=1}^N |w_i - \hat{w}_i|}{N}$$

where N is the number of transects or widths, w_i is the width measured from the water polygons derived from S2MSI imagery, and $\hat{w}_i$ is the width measured from the water polygons derived from the high-resolution satellite imagery.

5.4 Results

5.4.1 Threshold Optimization, Assessment of Otsu's Method, and Effect of Resampling

The manually determined optimized thresholds (MT) used to distinguish water from land using each index method on S2MSI data are illustrated in Table 5-3. Across the four study locations, the methods that produced the smallest range in optimal thresholds were AWEI_SH and AWEI_BOTH. Both had a range of 0.2. The other methods' threshold ranges were not much higher at 0.3. A smaller range in optimal threshold is desirable when processing many tiles of imagery, as the optimal threshold would be less likely to vary from image to image. The optimal thresholds for AWEI_SH, AWEI_NSH, and AWEI_BOTH trended negative, while the optimal thresholds for NDWI and MNDWI were closer to zero.

Table 5-3: Optimized (manually determined) thresholds for each spectral index method and each of the four locations, and the impact of resampling on the success of LWIC.

Location (Water area)	Metric	NDWI	MNDWI	AWEI_SH	AWEI_NSH	AWEI_BOTH
Red River (2.34 km ²)	MT	-0.1	-0.1	-0.2	-0.4	-0.2**
	Resample*	-	Yes	Yes	Yes	Yes
Sylvia Grinnell River (2.11 km ²)	MT	0	-0.1	-0.1	-0.4	-0.1**
	Resample*	-	No	Yes	Yes	Yes
Rivière-Rouge (5.18 km ²)	MT	-0.2	-0.2	-0.1	-0.2	-0.1**
	Resample*	-	No	No	No	No
Fraser River (1.15 km ²)	MT	0.1	0.1	0	-0.1	0**
	Resample*	-	Yes	Yes	Yes	Yes
Threshold Range	-	-0.2 to 0.1	-0.2 to 0.1	-0.2 to 0	-0.4 to -0.1	-0.2 to 0

* Resample indicates the impact of resampling on CSI. "Yes" indicates that a higher CSI was achieved when the image was resampled to a finer resolution.

** These values represent the selected threshold for both AWEI_SH and AWEI_NSH.

The reliability of Otsu's method in selecting the most optimal threshold varied across the images and LWIC methods. Figure 5-4 shows the thresholds computed using Otsu's method (Otsu's threshold or OT), the manually determined optimized thresholds (MT), and the histogram of pixel values for each LWIC method at each study location. The hollow points along the histogram curves indicate the thresholds determined via Otsu's method, and the solid points indicate the thresholds determined manually through optimization. The legends at the top right of each graph show the difference between the OT and MT. The OT was the closest to the MT when using the MNDWI spectral index, where the mean absolute difference (represented by MAE) between the OT and MT across the four images was the smallest. The OT was consistently lower than the MT

when using both the AWEI_NSH and AWEI_SH spectral indices. The OT had largest difference from the MT when using the AWEI_NSH spectral index.

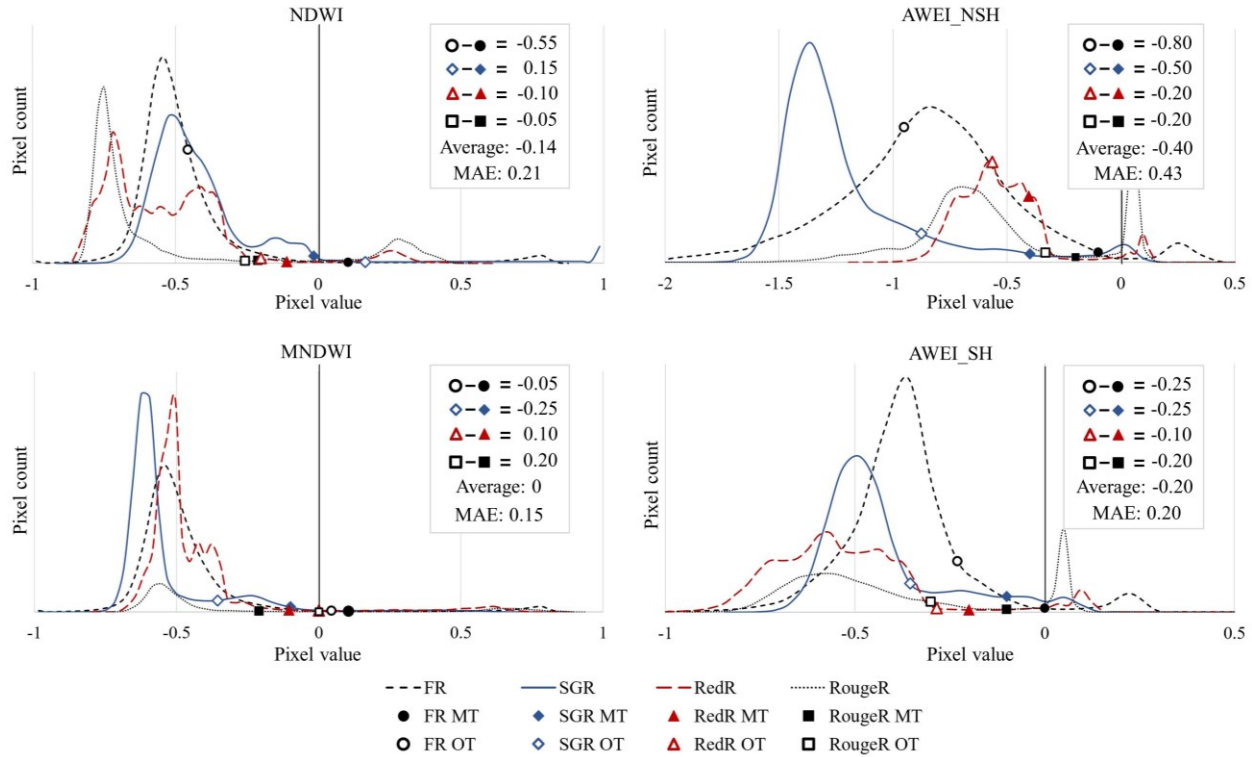


Figure 5-4: Manually determined optimal threshold between land and water classes compared to the threshold determined via Otsu's method.

When grouping the comparison of OT to MT by location rather than by LWIC method, the following average differences between OT and MT were calculated. For the RedR location, the average difference was -0.08 (-0.10, 0.10, -0.20, and -0.10 for NDWI, MNDWI, AWEI_NSH, and AWEI_SH, respectively). For the SGR location, the average difference was -0.21 (0.15, -0.25, -0.50, and -0.25), which was the second highest difference by location. For the RougeR location, the average difference was -0.06 (-0.05, 0.20, -0.20, and -0.20), which was the lowest difference by location. For the FR location, the average difference was -0.41 (-0.55, -0.05, -0.80, and -0.25), which was the highest difference by location and the difference between the OT and MT was consistently negative (i.e., OT was consistently higher than MT). Of the four locations, the FR location contained the most shadow due to the canyon walls. Additionally, the FR image's histogram had some of the largest separation of water and non-water pixels peaks (see the black dashed histograms in Figure 5-4). This large separation in histogram peaks, with the water peak (i.e., the peak in the positive pixel value range) amplitude being relatively small, may have created difficulties with Otsu's method selecting a suitable threshold. The threshold optimization results for all four locations are presented in Tables A2 to A6 in the supplementary material.

Resampling improved the results in the RedR, SGR, and FR images, but not in the RougeR image, as shown in Table 5-3. Resampling did not improve classification when the resulting extracted waterbody shorelines were not smoothed by this process. Rather, the densification of the pixels at the shorelines created unorganized, scattered, and misclassified water and non-water pixels that did not accurately represent the physical shoreline. The results of testing the effects of resampling at all four locations are presented in Tables A3 to A6 in the supplementary material.

5.4.2 Land Water Image Classification of S2MSI Imagery: Waterbody Area Basis

The best performing method of LWIC across the four sites was not consistent. Upon using the CSI metric to perform the comparison based on total waterbody area, MLC produced the best results for both the RedR and SGR locations. AWEI_SH produced the best results for the RougeR location. NDWI produced the best results for the FR location. Overall, SVM performed well at all four sites. MNDWI was not the best performing method at any of the four sites. The OE, CE, MA, and CSI results are presented in Figure 5-5, and the order of the methods' success in each image location are presented in Table 5-4. Upon summing all four CSI values resultant from each method and listing the methods from highest summed CSI to lowest summed CSI, the order of most successful to least successful method was as follows: AWEI_NSH (325.3%), AWEI_BOTH (319.4%), AWEI_SH and NDWI (318.2%), SVM (298.1%), MNDWI (297.2%), RT (280.9%), MLC (243.7%), and KNN (177.4%).

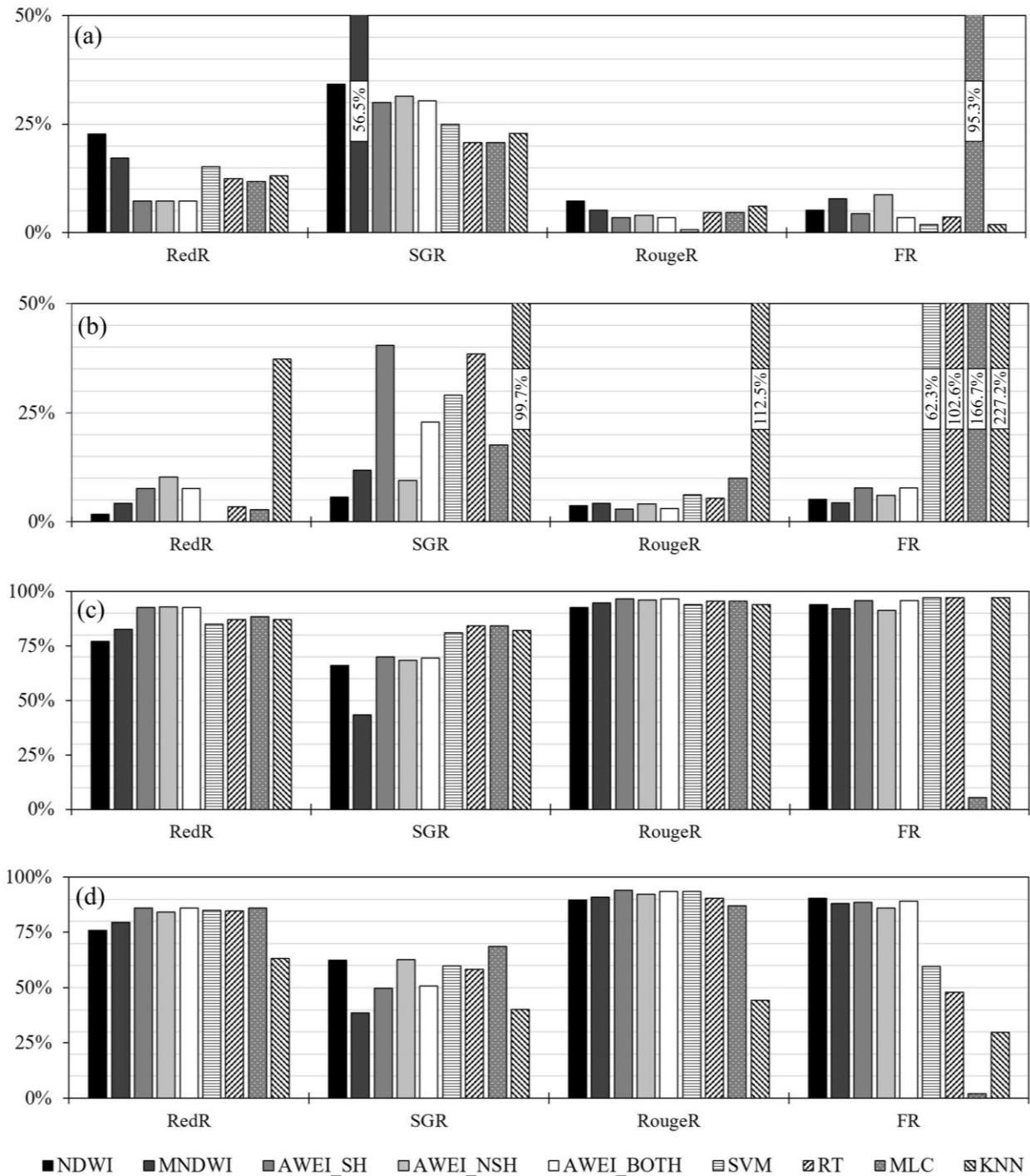


Figure 5-5: Classification accuracy of LWIC methods on S2MSI imagery based on (a) OE [%], (b) CE [%], (c) MA [%], and (d) CSI [%]. The OE, CE, and MA are normalized with the total waterbody area, and the values of the OE and CE outside of the 0% to 50% range are shown.

Table 5-4: Order of classification success for each method in each image location with 1 being best and 9 being worst.

Image Location	1	2	3	4	5	6	7	8	9
RedR	MLC	AWEI_BOTH	AWEI_SH	SVM	RT	AWEI_NSH	MNDWI	NDWI	KNN
SGR	MLC	AWEI_NSH	NDWI	SVM	RT	AWEI_BOTH	AWEI_SH	KNN	MNDWI
RougeR	AWEI_SH	AWEI_BOTH	SVM	AWEI_NSH	MNDWI	RT	NDWI	MLC	KNN
FR	NDWI	AWEI_BOTH	AWEI_SH	MNDWI	AWEI_NSH	SVM	RT	KNN	MLC

The best performing index for the RedR area (shown in Figure 5-6) was AWEI_BOTH, and all AWEI indices produced a CSI at least 5% higher than MNDWI or NDWI. The best performing classical machine learning based method was MLC, and MLC slightly outperformed AWEI_BOTH. KNN performed the worst overall with a large amount of scatter, creating a high CE. Following the organization of Figure 5-6, the results of each method are as follows. NDWI performed worst of the index methods due to high OE. In the threshold optimization exercise, NDWI was not able to capture the oxbow lakes as water without misclassifying the built up as water and thus increasing the CE and decreasing the CSI. MNDWI had similar issues, but with misclassifying the shoreline pixels along the river as land, leading to higher OE. AWEI_SH was able to detect most pixels correctly as water without misclassifying the built up as water, as indicated by the small OE and CE. AWEI_NSH produced a slightly higher CE than AWEI_SH because some land shoreline pixels were misclassified as water. The AWEI_BOTH result was very similar to AWEI_SH with similar OE and CE. Overall, MLC, SVM, and RT produced good results.

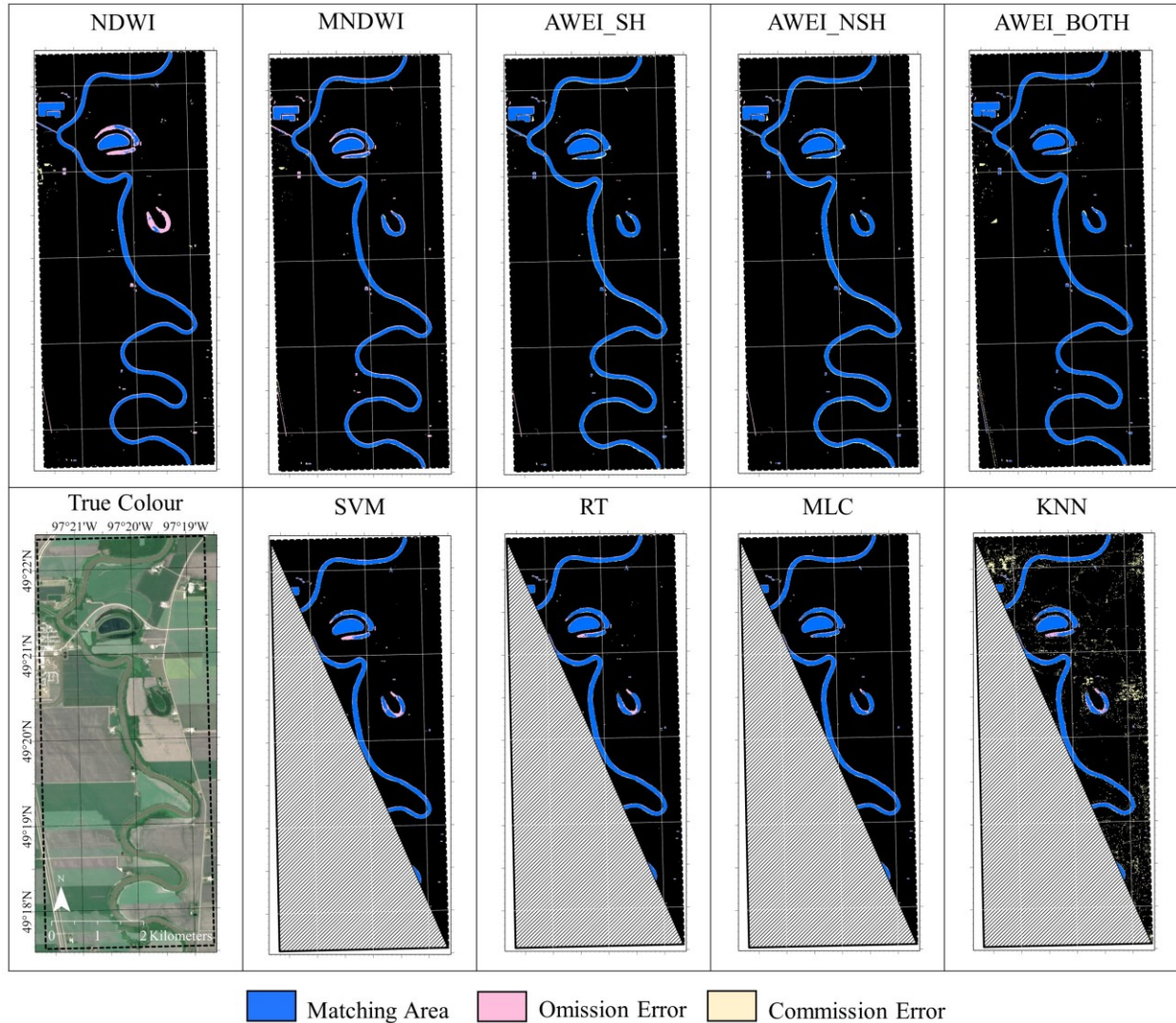


Figure 5-6: Red River S2MSI imagery classification results.

The best performing index for the SGR image area (Figure 5-7) was AWEI_NSH because it produced a lower CE compared to other indices, due to the correct classification of the runway. The best performing classical machine learning based method was MLC which produced the highest CSI by 10% compared to the other classical machine learning based methods. MLC also outperformed AWEI_NSH. The worst performing method was MNDWI. Following the organization of Figure 5-7, the results of each method are as follows. NDWI was a close second to the best index method because it produced the lowest CE. MNDWI produced the lowest CSI because of high OE and low MA while also misclassifying the built-up as water, resulting in high CE. The CE from the AWEI_SH method was also high. The AWEI_NSH method produced much better results than AWEI_SH or AWEI_NSH because it properly classified the runway. The AWEI_BOTH results were affected by the inclusion of AWEI_SH, which increased the CE

and CSI. For the classical machine learning based methods, all methods except MLC had high CE. Additionally, KNN produced a lot of speckle, resulting in further increased CE.

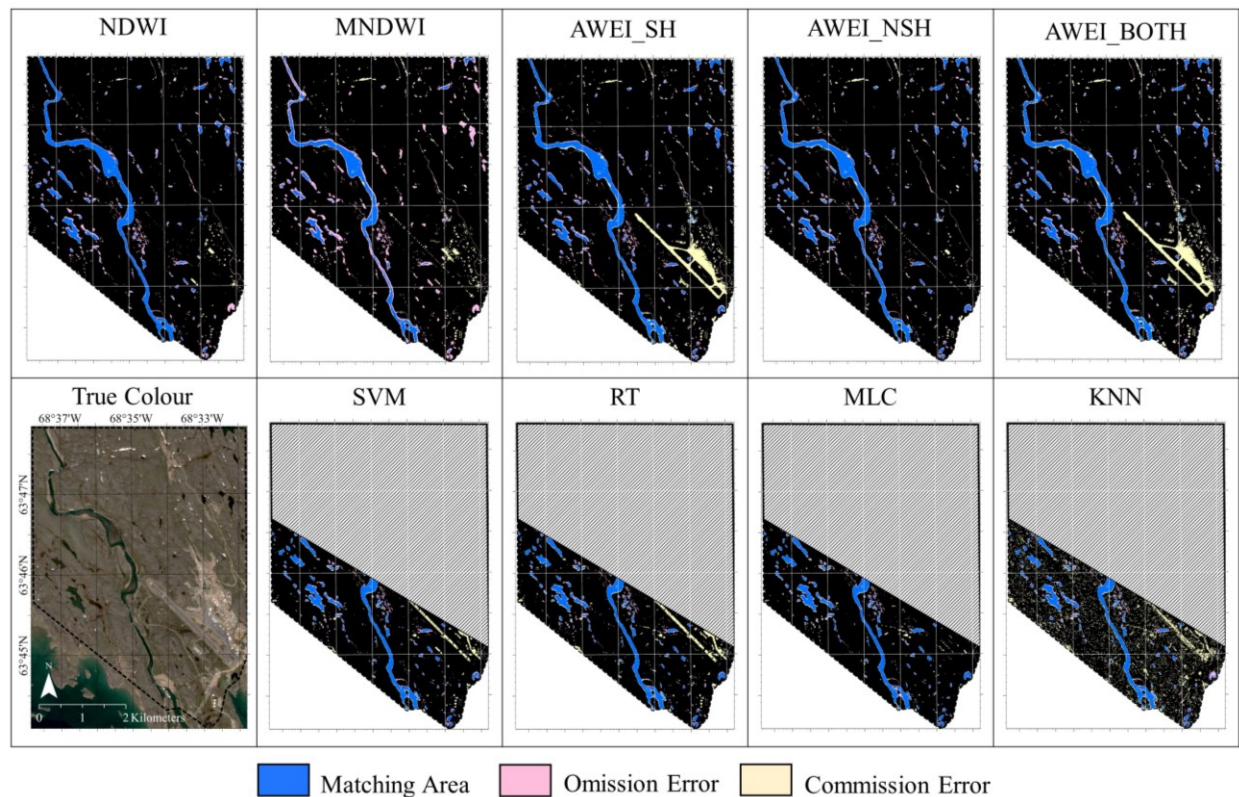


Figure 5-7: Sylvia Grinnell River S2MSI imagery classification results.

The best performing index method for the RougeR image area (Figure 5-8) was AWEI_SH. The best performing classical machine learning based method was SVM, but AWEI_SH performed best overall. The method that performed the most poorly was KNN, as it produced speckle. Following the organization of Figure 5-8, the results of each method are as follows. NDWI was the worst performing index method, due to high OE and CE. MNDWI also produced some CE, reducing the success of this method. AWEI_SH, AWEI_NSH, and AWEI_BOTH all performed well with varying success at extracting the location of the shoreline. SVM performed well at extracting the shoreline of both the Ottawa River and Rivière-Rouge in the validation area. RT performed well both at shoreline extraction and at producing a low CE. MLC shoreline extraction was acceptable, but SVM and RT produced better results. Additionally, MLC produced some misclassifications of the highway pixels. KNN performed the worst of all methods because of the speckle that was produced.

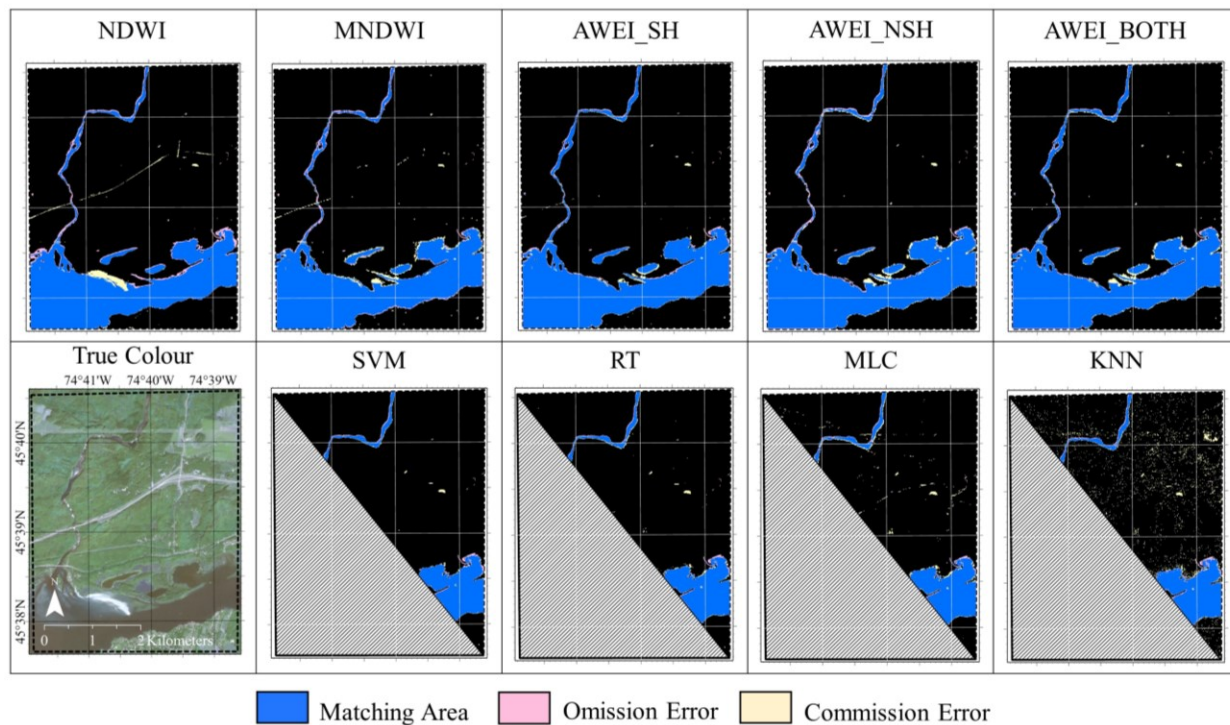


Figure 5-8: Rivière-Rouge S2MSI imagery classification results.

The best performing index method for the FR image area (Figure 5-9) was NDWI, but all spectral index-based methods were similarly successful. The best performing classical machine learning based method was SVM, but the indices performed better overall for this image. The worst performing method was MLC, which did not detect the river pixels as water, creating a high OE, and misclassified the shadows as water, also creating a high CE. SVM and RT produced classifications with high CE due to the shadows, and KNN produced high CE due to shadows as well as speckle.

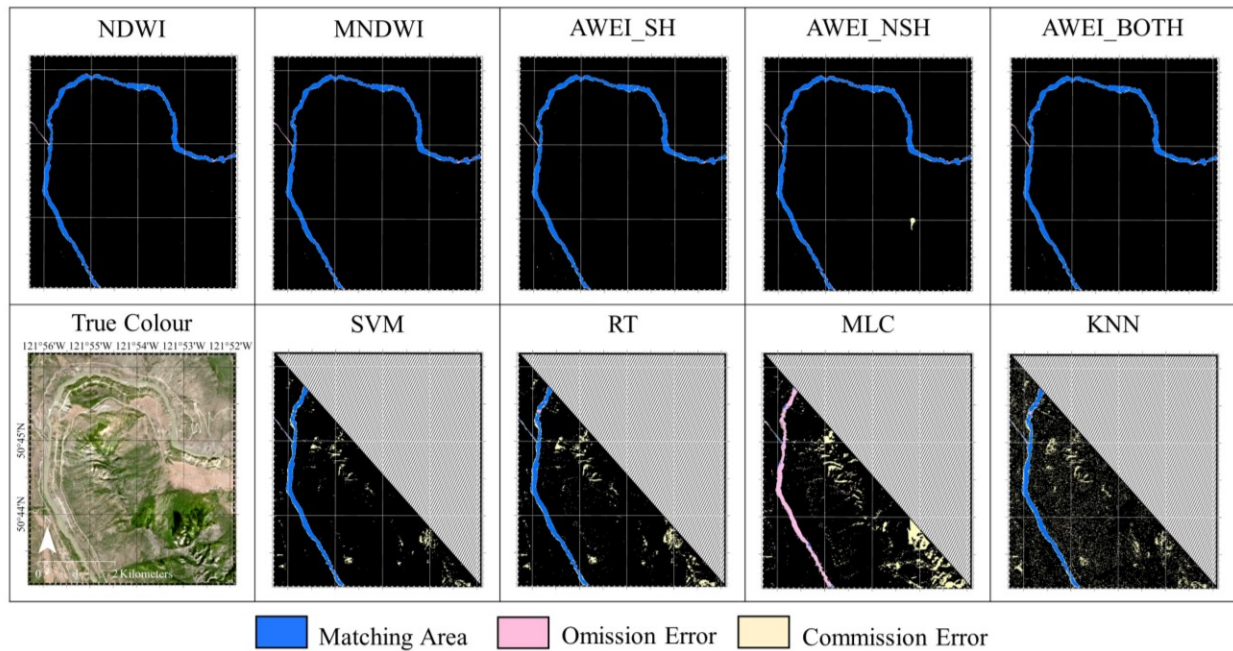


Figure 5-9: Fraser River S2MSI imagery classification results.

5.4.3 Land Water Image Classification of S2MSI Imagery: Waterbody Boundary Basis

River widths at 100m intervals extracted from the high-resolution validation data and extracted from the LWIC imagery were compared to quantify the success of each method at extracting the waterbody shorelines. The results are presented in Figure 5-10.

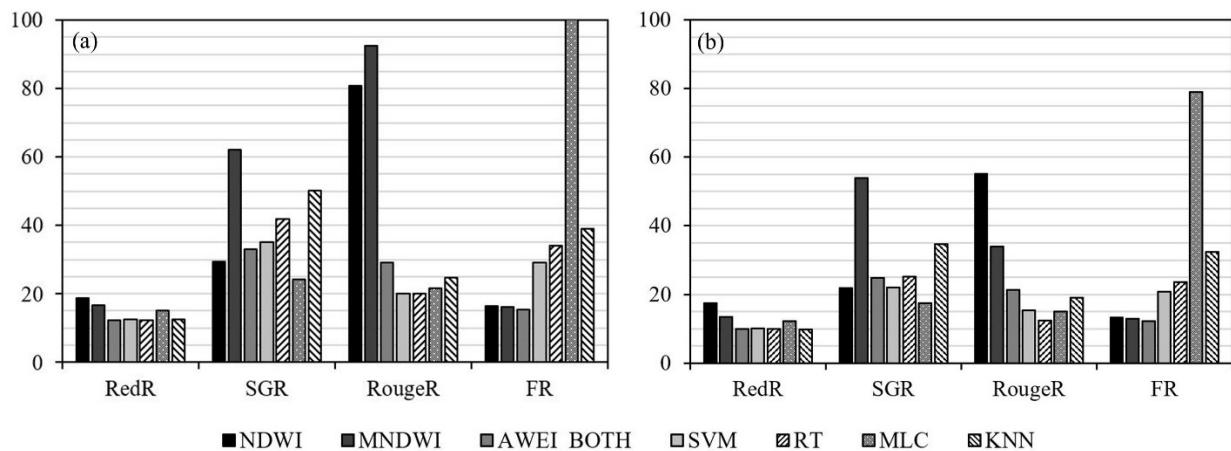


Figure 5-10: Classification accuracy of multispectral imagery based on (a) RMSE of river width [m] and (b) MAE of river width [m].

In this analysis, AWEI_SH and AWEI_NSH were not tested separately and AWEI_BOTH was used instead to represent the success of the AWEI indices. The results between the most optimal method in terms of total waterbody area and in terms of waterbody boundary

were not consistent across the four study locations. For the RedR area, the best performing method in terms of total waterbody area was MLC, whereas on a boundary-basis, the best performing method was AWEI_BOTH. AWEI_BOTH produced more CE in the RedR image, due to misclassifying buildings as water. This built-up was not included in the MLC validation area. AWEI_BOTH overall extracted the shoreline more accurately. Because of the uniformity of the river, all methods performed well using this metric. For the SGR area, the best performing method for both area- and boundary-based performance assessments was MLC; however, as shown with the CSI indicator in the waterbody area analysis, AWEI_NSH may have outperformed AWEI_BOTH in the SGR image. Thus, AWEI_NSH may have outperformed MLC on the waterbody boundary-basis if it had been tested separately from AWEI_BOTH. MLC had the lowest OE and second lowest CE, because the method captured most small waterbodies and did not misclassify the runway as water. Both the shorelines of the small waterbodies and the river were well defined by the MLC method. For the RougeR area, the best performing method based on waterbody area was AWEI_SH, but the best performing method based on the waterbody boundary was RT. RT had less OE and CE at the shorelines, and all classical machine learning-based methods performed better than the spectral index-based methods using the waterbody boundary basis. This may be due to the training area including more narrow areas of the Riviere Rouge and more wet sand and shallow vegetated shorelines on the Ottawa River in the training section of the image than the validation section. For the FR area, the best performing method for the waterbody area basis was NDWI while the best performing method for the waterbody boundary basis was AWEI_BOTH. All index methods extracted more accurate shorelines than the classical machine learning-based methods in the FR image, which had trouble with differentiating the shadows from water in the high relief areas along the river.

It is shown that the purpose of the LWIC can influence the best performing method. The best performing method of extracting the most accurate waterbody area in an image can be different than the best performing method of extracting the waterbody boundary. This will be the case if one method is more successful at minimizing the CE by correctly classifying non-water objects as water. This is because the CSI metric represents all of the CE and OE in the entire image, whereas the RMSE of the river width represents the CE and OE at the shoreline. The second metric would not include shadows, snow/ice, or any other difficult-to-classify non-water objects outside of the river area. Thus, the RMSE of river width gives a better measure of which method extracts the shoreline most accurately.

5.5 Discussion

5.5.1 Impacts of Method Optimization

When comparing the threshold derived from Otsu's method (OT) and the threshold derived from manual optimization (MT), it was found that the MAE was smallest for MNDWI between the four images. This suggests that Otsu's method generally produces a close-to-optimized threshold for MNDWI-based LWIC. For AWEI_NSH and AWEI_SH, the difference between OT and MT was consistently negative (i.e., OT was lower than MT). Thus, if OT was used with AWEI_NSH or AWEI_SH in previous work, it is more likely that the threshold was not optimized. This may have skewed previous results to indicate that the AWEI indices performed more poorly than other indices, such as MNDWI, if thresholds were estimated using Otsu's method. Likewise, previous studies have illustrated that the success of LWIC methods is dependent on suitable threshold selection, and automated threshold selection algorithms vary in their success to select a suitable threshold (Karaman, 2021; Sekertekin, 2021). The analysis of manually optimized thresholds and automated threshold selection algorithms could be further refined by iteratively evaluating other threshold values within the range of tested values at smaller intervals (e.g., iteratively adjust and evaluate threshold values in increments of 0.05 or 0.01, as opposed to 0.1). Previous literature had found that resolution increase by fusing imagery from 10m to 5m improved classification accuracy (Manaf et al., 2016), but this is likely image and location dependent. The result of resampling the resolution of the 20m bands (SWIR1 or band 11 and SWIR2 or band 12) to 10m to match bands 2, 3, 4, and 8 was inconsistent between images. Adjustment of the training and validation ratio for the machine learning-based LWIC methods may improve the quality of the surface water maps produced if more training data is available. A sensitivity test was performed with SVM by varying the training/validation ratio from 50/50 to 75/25. Additionally, the images included in the training data were adjusted such that the RedR, SGR, and FR images were used to train the model and the model was validated on the RougeR image. The resulting surface water map produced a slightly lower CSI (93.6% to 91.2%), and thus a slightly lower quality surface water map. The total percentage of MA increased, but both the OE and CE also increased. From this test, it cannot be understood if the change in the CSI is due to the change in the training/validation ratio or the change in the content of the training data. This example illustrates the need for further evaluation of training and validation ratios and improved understanding about the relationship between the quantity and content of training data and the resulting quality of surface water maps.

5.5.2 Influence of Imagery Characteristics on Surface Water Maps

Because of the method used to quantify the error of each LWIC method (i.e., CSI and RMSE of widths instead of the kappa coefficient approach), the characteristics and objects in the images that caused difficulties for successful LWIC could be observed. A summary of these findings is illustrated in Table 5-5.

Table 5-5: Summary of objects and characteristics present in the four images and the recommended (✓) or not recommended (✗) methods to support accurate LWIC when these objects and characteristics are present.

Image Characteristic	NDWI	MNDWI	AWEI_S H	AWEI_ NSH	SVM	MLC	RT	KNN
Built-up				✓				
Shallow Vegetated Shorelines			✓			✓		
Wet Sand	✗							
High Albedo Surfaces	✓					✓		
Mountain or Cliff Shadows					✗	✗	✗	✗
Shadows on Water				✓				
Narrow Waterbodies		✗	✓					

The effect of built-up being present in an image was inconsistent across the LWIC methods tested. Overall, the method that performed best at differentiating built-up from water across the images was AWEI_NSH, which was able to successfully classify the runway as land in the SGR image as shown in Figure 5-11, the town in the SGR image also shown in Figure 5-11, the highway in the RougeR image, and the town in the RedR image.

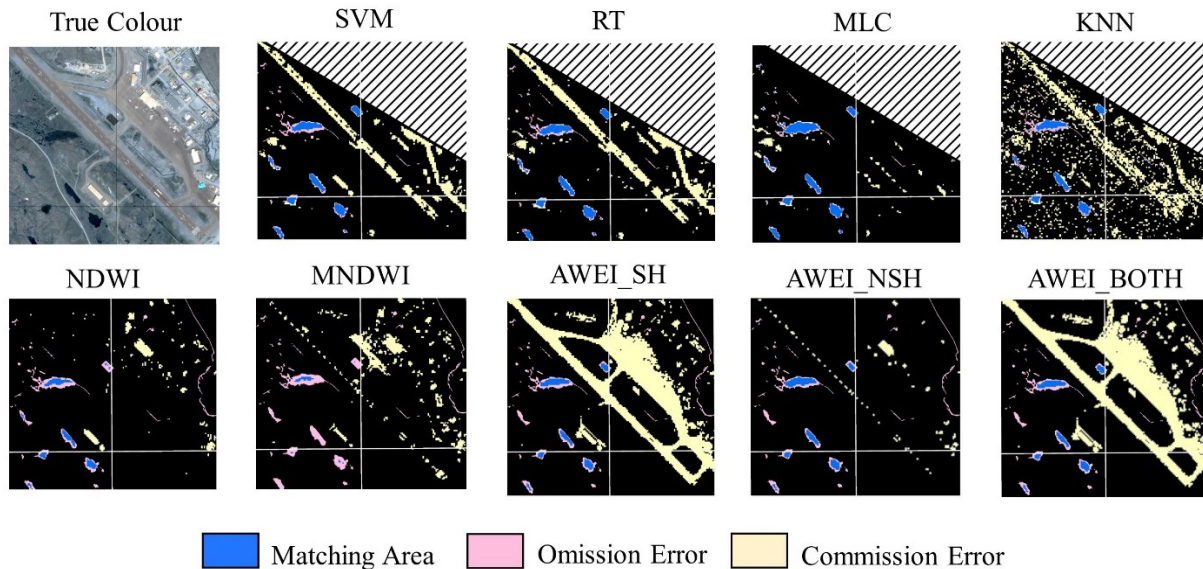


Figure 5-11: Built-up classification results from the SGR image area.

AWEI_SH could not differentiate the runway in the SGR image from water but did not struggle with the highway in RougeR or town in RedR. NDWI struggled with town buildings in the RedR image and the SGR image, and the highway in the RougeR image, but not the runway in the SGR image. The effect of town buildings in the RedR image could not be studied for the classical machine learning-based methods. In the SGR image, the MLC had the least amount of error caused by built up but, conversely, had the most amount of the highway in the RougeR image misclassified as water.

Shallow shorelines with vegetation caused issues for all methods, but could be minimized most with AWEI_SH, which performed well in the RougeR image with both the Ottawa River and Rivière-Rouge and the oxbow lakes in the RedR image, as shown in Figure 5-12. The effect of shallow shores with vegetation was not consistent across the indices: NDWI and MNDWI produced increased OE while AWEI_NSH produced increased CE in areas where shallow, vegetated shores were present. MLC produced the least amount of error caused by shallow vegetated shores in the RedR image, while the other classical machine learning-based methods had increased OE caused by the vegetated shorelines. None of the classical machine learning-based methods had difficulty extracting the vegetated shoreline in the RougeR image, likely because the methods were adequately trained on areas that had shallow vegetation.

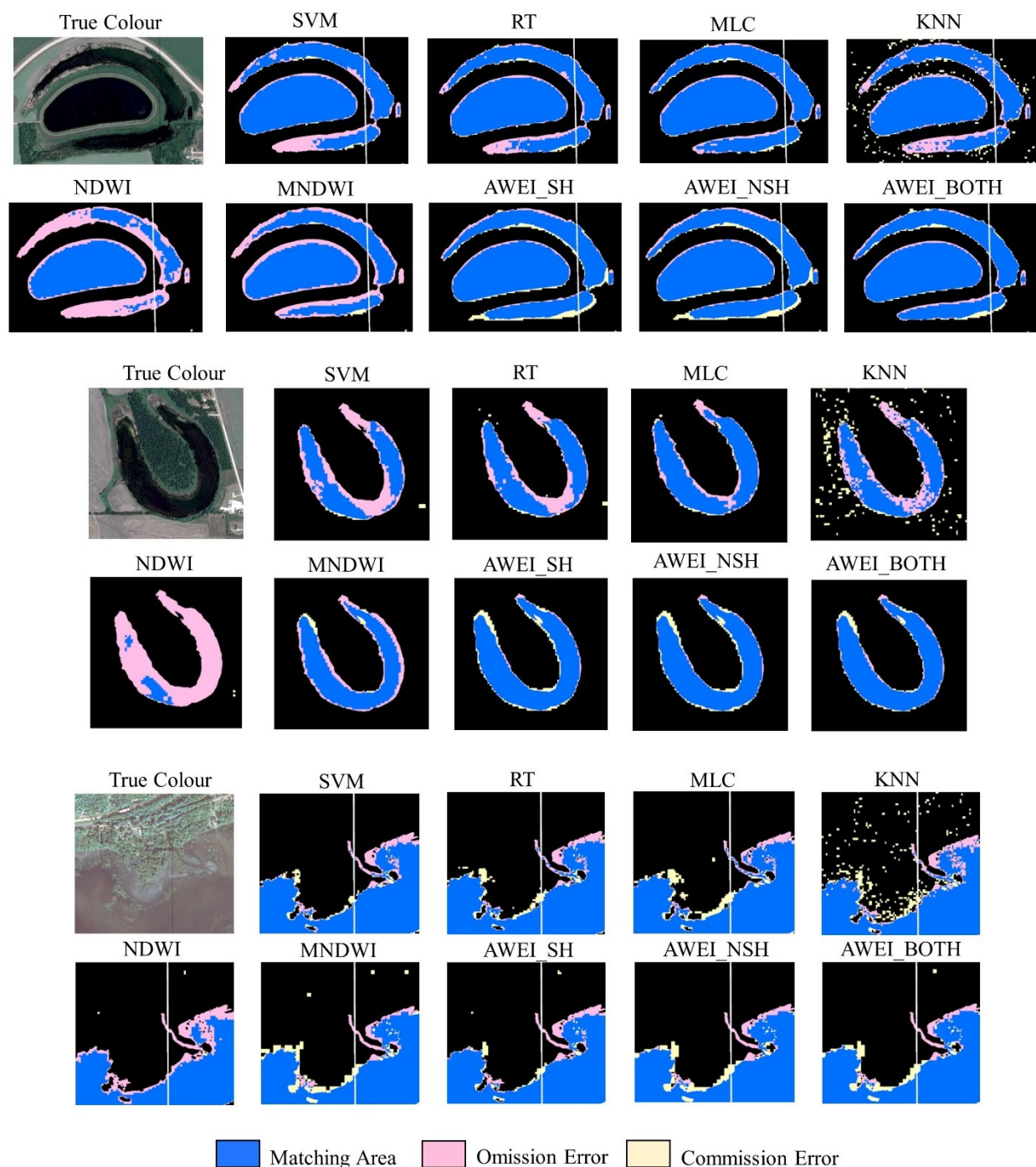


Figure 5-12: Shallow vegetated shoreline classification results in the RedR (top and middle) and RougeR (bottom) image areas.

Wet sand was able to be differentiated from water with all spectral index-based methods, except for NDWI, which misclassified areas with wet sand as water, increasing the CE. Wet sand was not present in any other image than the RougeR image on the Ottawa River shoreline. Thus, the findings could not be compared across imagery to

understand if NDWI consistently misclassifies areas with wet sand. Additionally, the wet sand area was not included in the validation area for the classical machine learning-based methods.

High albedo surfaces, especially snow and ice shown in Figure 5-13, caused issues for all LWIC methods tested. Snow was present in only the SGR image, so it could not be compared across sites for consistency. NDWI had the least amount of error caused by snow/ice surfaces in the SGR image compared to the other spectral index-based methods, but still was not able to completely differentiate snow and ice from open surface water. The MLC method was able to reduce the amount of error caused by snow and ice surfaces, which is consistent with the MLC results of other high albedo surfaces in the image (town buildings).

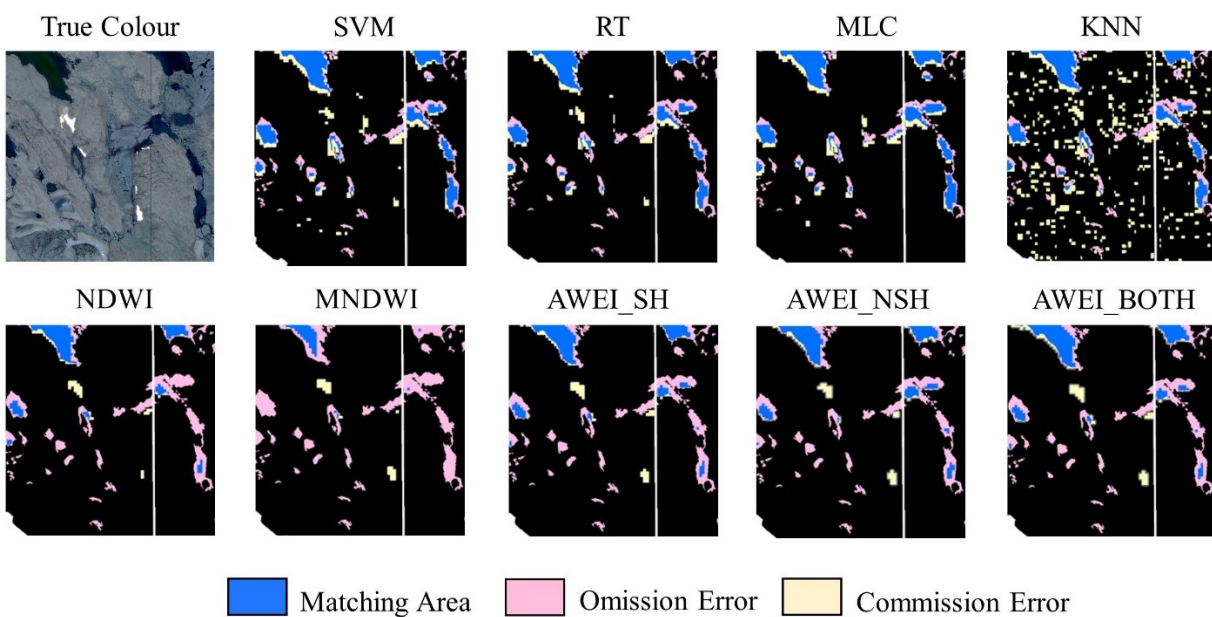


Figure 5-13: Snow and ice classification results from the SGR image area.

Dark shadow, caused by cliffsides, caused errors for all methods where the shadows were covering the water surface. In these instances, the water was misclassified as land. This finding indicates that shadows on water surfaces caused by dense clouds will cause misclassification by OE as well. AWEI_NSH produced the least amount of OE when cliff shadows were present on the waterbody, but it was also the only spectral index-based method that had a portion of mountain shadow that caused CE in the same FR image. No other images included significant shadowed areas, so this could not be compared across images. All classical machine learning-based methods produced some CE due to mountain and cliff shadows in the FR images as shown in Figure 5-14, even though the methods were trained on the opposite side of the image that also included shadows, though fewer shadows were present on the training side of the image. The MLC

method was not able to detect the waterbody in the FR image. This is likely because the MLC tool in ArcGIS Pro may only consider the class means of the “primary” band of imagery (i.e., NIR in this study). When a second band of imagery (i.e., green in this study) is added, the class means do not appear to be adjusted. Thus, if the second band of imagery changes the class means significantly, wide-spread misclassification occurs, as illustrated in Figure 5-14.

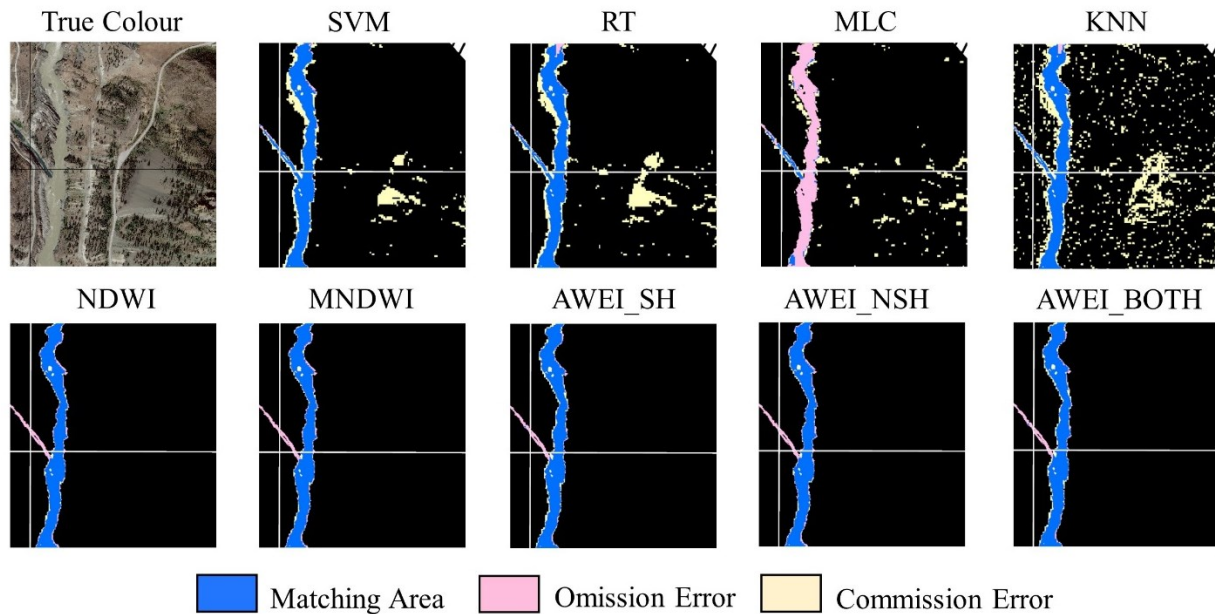


Figure 5-14: Shadow classification results from the FR image area.

Narrow waterbodies, particularly in the RougeR image illustrated in Figure 5-15, are inherently difficult for LWIC of S2MSI imagery due to pixel resolution constraints. AWEI_SH comparatively was able to detect more of the narrow locations of the Rivière-Rouge in the RougeR image than the other spectral index-based methods, though all methods created disjointed river water polygons at locations with river widths smaller than 40m.

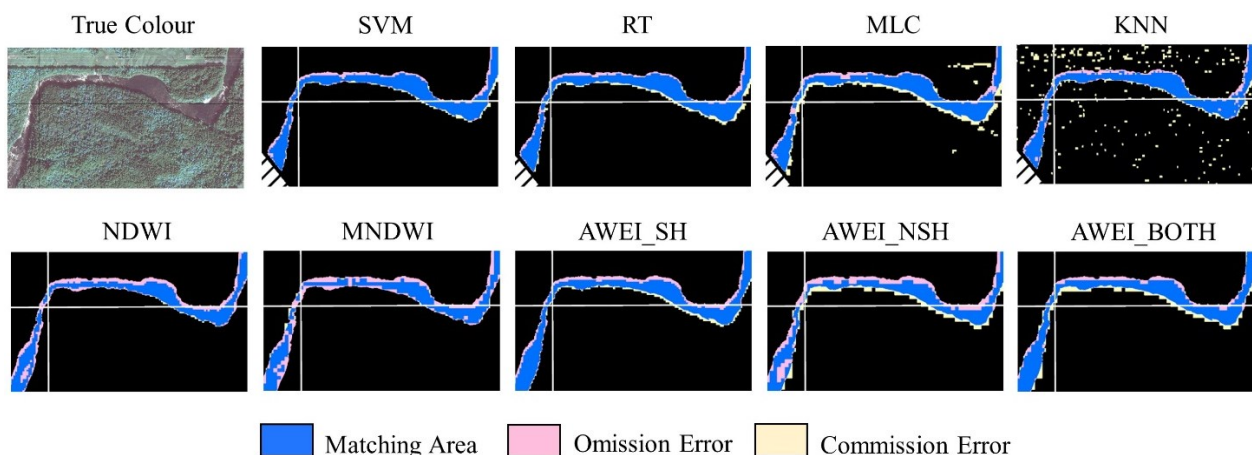


Figure 5-15: Narrow waterbody classification results from the RougeR image area.

This is also the case for the Sylvia Grinnell River in the SGR image, although NDWI also performed adequately to detect the narrow areas (sub-40m width) of the river. MNDWI performed poorly at extracting the narrow waterbodies in both the RougeR and SGR images, as illustrated by the RMSE and MAE. MLC produced disjointed waterbody polygons at narrow locations of rivers in the SGR image, as well as misclassification of rapids as non-water pixels, but the other classical machine learning-based methods did not have these issues. This was also the case for the RougeR image in which the MLC struggled the most to produce continuous water polygons at the narrow locations, but all classical machine learning-based methods did struggle with this in the RougeR image.

The different types of soil and vegetation across the four images did not seem to influence the success of the LWIC methods. The different types of water colour and turbidity also did not seem to influence the LWIC results across the images. When the thresholds were optimized for the spectral index-based methods, the methods were just as successful at LWIC for high turbidity waters (in the RedR image, averaging 303 mg/L) as they were for low turbidity waters (in the RougeR image, averaging 37 mg/L). Turbid waters differ from green and clear water with a higher spectral reflectance in the NIR band. Bare soil also has its highest spectral reflectance in the NIR band; however, the reflectance of bare soil is much higher than turbid water (Sun et al., 2012). Thus, turbid water is not difficult to differentiate between other image characteristics, such as bare soil, when the NIR band is included in the classification. Additionally, green water, or water containing chlorophyll, differs from clear water with its highest spectral reflectance in the NIR band. Green water and terrestrial vegetation have low red reflectance and high NIR reflectance, but green water has much lower reflectance of the NIR band compared to vegetation (Sun et al., 2012). Thus, green water is also not difficult to distinguish from other image characteristics, such as vegetation, if the NIR bands is included in the classification.

A limitation of this study consisted of the fact that temporal changes at each study location, and potential impacts on the quality of surface water maps produced, were not evaluated in this study. Future research focused on assessing LWIC methods under different seasonal conditions would provide valuable context to further inform LWIC strategy.

5.5.3 Comparison to Other Studies' Findings

To understand how this study's findings align with the current understanding of LWIC methods' success, the order of most to least successful LWIC method for this study and others is compared in Table 5-6. A general trend exists for the machine learning LWIC methods where SVM is the most successful with RT, or random forest (RF) or decision tree (DT), second and MLC third. This trend is also illustrated in our study

findings when considering the mean CSI across the four image areas. Similar comparison-based studies did not evaluate and compare the KNN algorithm. When comparing spectral index methods to machine learning methods, our study found the spectral index methods to outperform the machine learning methods. However, it has been shown that an increased number of training samples may improve the output of machine learning models beyond that of spectral index methods, specifically NDWI (Ireland et al., 2015). However, at a lower number of training samples, NDWI was shown to outperform SVM (Ireland et al., 2015). This highlights the fact that machine learning techniques are only useful if a good amount of training data is available, and successful global application of one trained model to other imagery may vary.

The trend for most successful to least successful spectral index-based methods is less clear than it is for machine learning LWIC methods. NDWI out-performed MNDWI in three studies, and NDWI was outperformed by MNDWI in a different three studies. Fewer studies compared AWEI_SH and AWEI_NSH than NDWI and MNDWI with only four studies examining either AWEI_SH or AWEI_NSH and 14 studies examining either NDWI or MNDWI. Additionally, a direct comparison to some of the studies that varied bands of imagery (Doña et al., 2016) and employed combinations of machine learning and spectral index methods (Yilmaz et al., 2023) is not possible. The range in the trend most to least successful spectral index methods is likely due to the range of image characteristics, imagery pre-processing, and thresholding techniques applied in each of the studies. For example, five studies in Table 5-6 employed Otsu's method, six studies adjusted the threshold manually (as performed in this study), two studies did not mention the threshold procedure used, one study used default thresholds (e.g., 0 for NDWI and MNDWI), and two studies used a variety of machine learning algorithms (e.g., RF, MLC, K-means, etc.). As shown in our analysis comparing the Otsu derived threshold to the manually adjusted threshold, and in the works by Sekertekin (2021) and Karaman (2021), the choice of threshold selection algorithm not only can determine the success of the method, but the combination of certain spectral indices with certain thresholding algorithms are more likely to produce accurate surface water maps than others. For example, in this study Otsu's method was more likely to produce an optimized threshold for MNDWI than it was for AWEI_SH or AWEI_NSH.

It is also important to note that this study's order of most to least successful LWIC methods represents an average over the four image areas. For example, although AWEI_NSH was the most successful overall, it was not the highest performing method in any of the individual study images. This suggests that a single image area cannot determine which LWIC is most successful overall, and rather, the success of each LWIC method depends on the imagery characteristics that each LWIC method is more likely to properly or improperly classify, as illustrated in Table 5-5.

Table 5-6: Order of classification success for this study compared to other studies. All acronyms for other study methods are included in the appendix in Table A7. The methods in dark red are the methods explored in this study.

Study	Best	→	→	→	→	→	→	→	→	→	→	→	→	Worst
This study ** 1	AWEI_NSH	AWEI_BOTH	AWEI_SH	NDWI	SVM NIR+Green	MNDWI	RT NIR+Green	MLC NIR+Green	KNN NIR+Green	-	-	-	-	-
Alcaras et al. (2022) 1	NDWI	MNDWI	RGR	NDVI	EVI	NRR	-	-	-	-	-	-	-	-
Aroma and Raimond (2021) * a 2	NDWI	FCM Band 5	K-mean Band 5	ARKFCM Band 5	K-means Band 6	ARKFCM Band 6	SLIC-SUPER	FCM Band 6	MNDWI	ARKFCM Band 3	FCM Band 3	K-means Band 3	-	-
Dona et al. (2016) 2	GP Band 4	(1) Band 4 (2) Mahalanobis Bands 3,4 (3) SVM Cubic Bands 3,4	(1) ISODATA Bands 3,4 (2) ANN Bands 1-5,7 (3) SVM M Gauss Bands 3-5	SVM Linear Bands 3-5	SVM Course Bands 3-5	(1) MLC Bands 3,4 (2) SVM Linear Bands 1-5,7 (3) SVM Course Bands 1-5,7	(1) MNDWI (McFeeters)	MLC Bands 4,5	(1) I_CEDX (2) Band 5 (3) SVM Quadratic Bands 3-5 (4) SVM F Gauss Bands 3-5	Minimum Distance Bands 4,5	NDWI (Gao)	(1) K-means Bands 4,5 (2) K-means Band 4	(1) NDVI (2) SAVI	Parallelepiped All Combinations
Pena-Reguerio (2020) * 1	NDWI	B_Blue	AWEI_SH	MNDWI	AWEI_NSH	CEDEX	RE-NDWI	-	-	-	-	-	-	-
Zhang et al. (2022) * 2	(1) NDWI (2) CIWI	NIR Band	-	-	-	-	-	-	-	-	-	-	-	-
Hafiza Wajiha Khalid et al. (2021) * a 2	LBWEI	NDWI	NWI	WRI	MNDWI	NDMI	AWEI_SH	-	-	-	-	-	-	-
Yilmaz et al. (2023) a 1 2	RF (Vis + NIR)	RF (Vis + NIR + NDWI)	RF (Vis + NIR + MNDWI)	MLC (Vis + NIR + NDWI)	MLC (Vis + NIR + MNDWI)	MLC (Vis + NIR)	K-means (Vis + NIR + NDWI)	K-means (Vis + NIR)	K-means (Vis + NIR + MNDWI)	-	-	-	-	-
Ireland et al. (2015) 2	rkFDA RBF	SVM RBF	rkFDA Linear	SVM Linear	NDWI	-	-	-	-	-	-	-	-	-
Feyisa et al. (2014) ** 2	AWEI	MNDWI	MLC	-	-	-	-	-	-	-	-	-	-	-
Senel et al. (2020) 1 2	(1) AWEI_NSH , Landsat (2) AWEI_NSH , Sentinel	(1) MNDWI , Sentinel (2) MLC , Sentinel	NDWI , Sentinel	(1) MNDWI , Landsat (2) AWEI_SH , Landsat	(1) NDWI , Landsat (2) TCWI, Landsat	MLC , Landsat	-	-	-	-	-	-	-	-

				(3) AWEI_SH, Sentinel	(4) TCWI, Sentinel										
Feizizadeh et al. (2023) ^{a 2}	SVM	RF	CART	-	-	-	-	-	-	-	-	-	-	-	-
Li et al. (2022) ^{* 2}	SVM	CART	Object-Oriented	Deep Learning	NDWI	-	-	-	-	-	-	-	-	-	-
Manaf et al. (2016) ³	SVM	Neural Network	MLC	Mahanalobis Distance	Minimum Distance	Parallelepiped	-	-	-	-	-	-	-	-	-
Otukei and Blaschke (2010) ^{a 2}	DT	MLC (All Bands)	SVM (Reduced Bands)	SVM (All Bands)	MLC (Reduced Bands)	-	-	-	-	-	-	-	-	-	-
Singh and Pandey (2021) ^{a 2}	RT	SVM	MLC	-	-	-	-	-	-	-	-	-	-	-	-
Sun et al. (2012) ²	New pixel-based method	MLC + NIR	MNDWI	New integrated method	NDWI	-	-	-	-	-	-	-	-	-	-
Thati et al. (2021) ^{* a 2}	MNDWI + ISODATA	MNDWI + Otsu	MNDWI + K-means	MNDWI + Threshold segmenting	-	-	-	-	-	-	-	-	-	-	-

* Study completed with multiple image areas

** Study completed with multiple image areas with a variety of landcover characteristics

^a Study completed in multiple seasonal conditions or different years

¹ Study completed with Sentinel-2

² Study completed with Landsat

³ Study completed with SPOT

5.6 Conclusions and Recommendations

Five methods of spectral index-based LWIC and four methods of classical machine learning-based LWIC on S2MSI imagery were compared across four diverse locations in Canada. The methods and imagery were chosen because of their regular use in remote sensing applications, especially in surface water detection. The purpose of this comparison was to provide recommendations of the best performing method of LWIC for future surface water detection research. The following list outlines the main conclusions of this work:

- The spectral index **AWEI_NSH** was the overall most successful method of LWIC across the four study locations. **SVM** was the most successful machine learning method of LWIC across the four study locations, though it was outperformed by most of the spectral indices.
- Threshold selection is important. The threshold optimization exercise performed in this study showed that optimizing thresholds is important before comparing the results of LWIC methods against each other.
- The most successful LWIC method was not consistent across the sites and the order of most to least successful LWIC methods across the sites was also not consistent. This illustrates that each method's success is dependent on the characteristics of the image area.
- It was not consistent across the four study locations whether spectral index-based methods or classical machine learning-based methods produced the highest accuracy surface water maps.
- Certain image characteristics (i.e., built-up, shallow vegetated shorelines, wet sand, high albedo surfaces, shadowy areas, and narrow waterbodies) were more likely to cause classification errors. For correctly classifying **built-up** as land pixels, **AWEI_NSH** produced the most successful LWIC. For **shallow vegetated shorelines**, **AWEI_SH** or **MLC** were both successful at classifying the vegetated water as water pixels. For images including **wet sand**, **NDWI** is not recommended, but this was not tested across multiple images, so this conclusion is not as strong comparatively. For **high albedo surfaces**, such as **snow and ice**, **NDWI** and **MLC** were able to minimize the amount of snow and ice classified as liquid surface water but not completely. For **shadowy images**, spectral index-based methods overall perform successfully and better than classical machine learning-based methods. For **narrow waterbodies**, **AWEI_SH** was able to correctly detect more of the shoreline than the other methods.
- The most optimal method of detecting surface water overall in the image may not be the most successful at detecting the most representative waterbody boundary. Thus, it is important to consider what the purpose of the LWIC is when selecting an optimized approach.

The following is the future recommended work based on the limitations and findings of this study:

- Analysis of the four locations in different seasonal conditions was not performed; thus, in future work it may be interesting to understand if the best performing method can change in different images at the same location.
- Sensitivity testing on the training/validation ratio of the classical machine learning methods was performed only for one additional case beyond the 50/50 spatial split applied in this study. This ratio is an important consideration when performing surface water mapping, as the results can vary based on the training data available. Thus, the training/validation ratio of classical machine learning methods should be tested and considered in future works.

Chapter 6. River Hydrokinetic Resources in Canada

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Ferguson, S., Rennie, C.D., Cousineau, J., Burcher, R., Nistor, I., 2026. High-resolution mapping of river hydrokinetic energy resources in Canada using remote sensing. *Renew. Energy* 256, 123970. <https://doi.org/10.1016/j.renene.2025.123970>

Abstract:

Many remote and northern communities rely on imported diesel for electricity, facing high costs, logistical challenges, and environmental risks. River hydrokinetic energy (HKE), which generates electricity from flowing water without dams unlike conventional hydropower, offers a lower-impact, locally available renewable alternative. However, identifying promising HKE sites typically requires extensive and costly field data collection, creating a barrier for development. To address this gap, the authors present the first national, high-resolution database of river HKE across Canada, covering all river segments with flows exceeding 100 m³/s. The database includes cross-sectional measurements and estimates of flow, depth, width, velocity, and power at up to 100-meter intervals, allowing communities and developers to identify areas with strong local energy potential before committing to field investigations. Validation against field and modelled data confirmed good agreement, supporting its reliability for preliminary site screening and policy planning. By capturing energy-enhancing river features such as lateral constrictions and steep gradients, this dataset provides a valuable tool for accelerating the transition from diesel-based electricity to renewable HKE, particularly in remote and rural communities.

Keywords: Renewable river hydrokinetic energy; small hydropower electricity; cloud processing satellite imagery; run-of-the-river hydroelectricity; sentinel-2 remote sensing river widths; in-stream micro turbine

6.1 Introduction

The ability to access and develop sources of electricity is essential for human well-being, and demand for electricity is increasing. Currently, fossil fuels contribute the majority of electricity sources (Bose, 2010; Yadav et al., 2023), but there is a demand for alternative, sustainable energy sources (Shahsavari and Akbari, 2018). The negative environmental impact of fossil fuel-based electricity and the depletion of fossil fuel reserves drive this change (Panwar et al., 2011). In particular, rural populations may either have no access to electricity or may be reliant on fossil fuel resources, resulting in limited access to education and information, lower living standards, potentially restricted

community development, and poor community health (Agu et al., 2023; Karanasios and Parker, 2018). River hydrokinetic energy (HKE) may be a promising solution to these climate change and energy availability crises (Vermaak et al., 2014). River HKE is generated by introducing a turbine into the flow of a river, converting the natural flow of the river into electricity. Importantly, unlike dams or flow diversions, the river's flow is not changed significantly; as such, the technology has fewer negative ecological and environmental impacts compared to traditional hydropower (Cada et al., 2007), such as sediment starvation (Kondolf et al., 2014), hydropeaking (Batalla et al., 2021), and significant changes to the river's hydrological cycle from large evaporation losses (Li et al., 2025). For one example, alteration of a river's sediment transport capacity is detrimental to nutrient transport to downstream ecosystems (Fantin-Cruz et al., 2020). A hydrokinetic turbine's impact on the river's natural sediment transport capacity is miniscule compared to dam-based hydropower (Hill et al., 2016).

Renewable HKE technologies present an opportunity for remote Indigenous communities to transition from diesel-based electricity to renewable sources or hybrid renewable-diesel sources to improve community health and bolster Indigenous self-determination (Karanasios and Parker, 2018). Because hydrokinetic turbines are comparatively less obstructive than traditional dam-based hydropower, communities that have tight ties to the nearby riverine environment due to cultural significance, food security, or other reasons may find this type of renewable energy more attractive. River HKE is maybe most promising for Indigenous, rural, and remote communities that currently rely on diesel fuel in Canada (Government of Canada, 2016; Vermaak et al., 2014) and globally (Awandu et al., 2025). Some of these remote communities are located near rivers which, under certain conditions, could produce meaningful amounts of electricity for the community. For example, the river hydrokinetic turbine installed in the remote community Igiugig, Alaska currently provides half of the community's required electricity during peak demand periods (Office of Energy Efficiency & Renewable Energy, Department of Energy, United States Government, 2021). Even the installation of HKE turbines in dam tailraces has the potential for notable power production, despite the possibility for the reduction in available hydraulic head (Tseng and Musa, 2025). However, identifying river sites which are feasible for HKE extraction can be difficult in remote areas; the field data collection campaign that is required to do a full assessment of the HKE resource is costly and time consuming, especially at a remote location (Kirby et al., 2023a). To facilitate this renewable technology's success and to ensure that it can be competitive with fossil fuels, up-to-date national datasets of river HKE must be available to aid communities and developers in identifying locations that are feasible for energy extraction so further site investigation can take place. The ultimate goal of this research is to reduce Canada's dependency on fossil fuels and bolster renewable HKE use by providing a novel dataset of river HKE resource estimates across Canada for developers and communities.

Previous large-scale (global or national) assessments of river HKE have relied on either application of Manning's equation to derive wide-scale estimates of velocity in the USA (Jacobson, 2012; Miller et al., 1986) or Canada (UMA Group, 1980) or have developed regression-based relationships based on the available measured hydrometric and river morphological data in Canada (Jenkinson and Bomhof, 2014) and globally (Ridgill et al., 2021). Compared to direct measurement of river characteristics, either from field data collection or remote measurement (satellite or aerial), empirical relationships like those used in previous HKE assessments have reduced accuracy. Furthermore, large-scale HKE assessments and resulting databases are uncommon, as the required data to perform such analyses are difficult to obtain at such a large spatial scale. Following a review of these large-scale HKE resource assessments, one suggested improvement to the accuracy of river HKE estimates was the direct measurement of channel geometry from remotely sensed data (Kirby et al., 2022a), compared to the previous approach of developing empirical relationships. In particular, measurements of river width from either optical or synthetic aperture radar (SAR) sources can be used to improve the accuracy of river velocity and HKE estimates. The present study addresses this gap by being the first HKE resource assessment of this scale using the estimation of river characteristics directly from satellite imagery. This database also contains the largest national database of river width measurements produced as of yet with multiple river width measurements available across different seasonal conditions (Allen and Pavelsky, 2018; Yamazaki et al., 2014). In addition to improving the accuracy of the estimates, the resolution of HKE databases must also be increased compared to previously developed databases to improve usefulness to communities and energy developers. The current maps of river HKE are reach-average based (e.g., average power across a 5 km river reach) (Jenkinson and Bomhof, 2014; Ridgill et al., 2021) and would benefit from becoming cross-section average based. Thus, the new methods applied in this study derive estimates of HKE on a finer scale compared to previous work. This work is a necessary step to improve HKE assessments, to develop and mature the technology, and to empower communities to benefit from this renewable energy source.

6.2 Data and Methods

6.2.1 Methodology Framework

The annual energy production (AEP) is generally used as a standard metric of HKE availability at a river site (IEC, 2019), as it represents the HKE availability across a typical year. In this study, seasonal variability of river flow is considered by using 17-point duration curves. Duration curves of flow (FDC), depth (DDC), velocity (VDC), and power (PDC) were developed and are available in the database (each point and associated flow exceedance percentage is listed in Table 6-2). HKE estimation for this study is based on the three equations below:

$$[6-1] \frac{P_K}{A} = \frac{1}{2} \rho v^3$$

$$[6-2] v = \frac{Q}{A} = \frac{Q}{w \times d}$$

$$[6-3] AEP = N_h \sum_{i=1}^{N_B} P_i B_i$$

where:

- P_K = hydrokinetic power [$\text{kgm}^2\text{s}^{-3}$]
- ρ = water density [kgm^{-3}]
- A = river cross-sectional area [m^2]
- v = flow velocity [ms^{-1}]
- Q = river flow [m^3s^{-1}]
- w = river width [m]
- d = river depth [m]
- AEP = the annual energy production [MWh/year]
- N_h = the number of hours of turbine operation in a year [hours/year]
- N_B = the number of points on the PDC [-]
- P_i = the theoretical power present at the point on the PDC [$\text{kgm}^2\text{s}^{-3}$]
- B_i = the width on the PDC that the point represents as a decimal probability [-]

Use of these equations presents some assumptions and limitations. A uniform rectangular channel shape is assumed with no turbulence and/or recirculation patterns that would alter the stream-wise velocity. Additionally, only the theoretical maximum resource is estimated using these equations, and thus the reduction in capturable power from turbine or transmission efficiency losses are not considered in the derived estimates.

As a visual representation of the calculations performed to develop the database, the methodology framework is presented in Figure 6-1, and the contribution of each data product is presented in Table 6-1. The contribution of each data source to the final HKE estimates are described in the following sections.

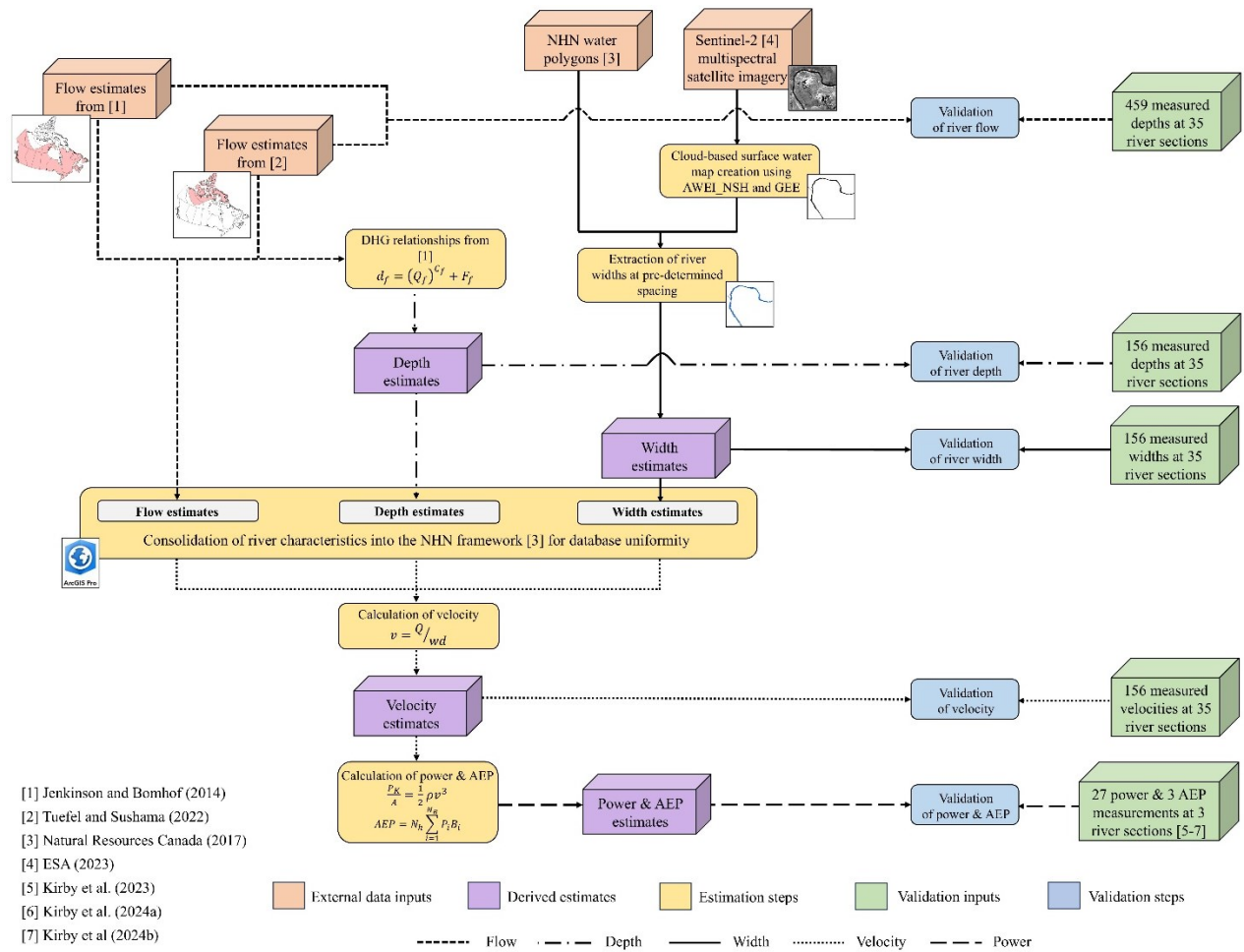


Figure 6-1: Study methodology framework. All acronyms in the figure are defined in the text.

Table 6-1: River characteristics data used in the estimation of HKE.

River Characteristic	Dataset	Coverage	Data Format	Temporal Coverage
Flow (Q)	Jenkinson and Bomhof (2014)	Sub-Arctic Canada	Polyline	17-point FDC
Flow (Q)	Teufel and Sushama (2022)	Canada	NetCDF	Daily flows for 20 years
Depth (d)	DHG Relationships from Jenkinson and Bomhof (2014)	Canada	Regression Relationships	Based on 17-point FDC
Width (w)	Sentinel-2 Multispectral Imagery (ESA, 2023)	Canada	Raster	2019-2022
Width (w)	National Hydro Network (2017)	Canada	Polygon	No Information

Flow lines	National Hydro Network (2017)	Canada	Polyline	No Information
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6.2.2 River Flow Data

River flow data from a previous iteration of the national HKE energy database for Canada (visualized in the Atlas of Canada – Remote Communities Energy Database, <https://atlas.gc.ca/rced-bdece/en/index.html>) were applied where available in sub-Arctic Canada (see top left of Figure 6-1 for coverage). To derive estimates of flow, Jenkinson and Bomhof (2014) employed multiple linear regression coupled with canonical correlation analysis (MLR-CCA), leveraging hydrometric gauge station data from Water Survey of Canada (WSC) to estimate flows at ungauged river locations. This method used watershed catchment similarities, such as soil characteristics, land cover, surficial geometry, and climate data, to extrapolate flow data. Regional flow estimation techniques were used to estimate a 17-point FDC for each stream segment.

However, flow estimates from this 2014 study were unavailable for the Canadian Arctic due to limitations in data and methods at the time. To address this gap, flow estimates for the Arctic regions were sourced from Teufel and Sushama (2022), which employed Environment and Climate Change Canada’s Global Environmental Multiscale Model (GEM) (Cote et al., 1998). This model provided hydrological data in NetCDF format at a 50 km resolution for the 1979-2016 period. The developers subsequently downscaled the data to a 5 km resolution using a modified version of the WATROUTE routing scheme (Sushama et al., 2021; Teufel and Sushama, 2022). The downscaling incorporated Manning’s equation, channel geometry assumptions, and data from the HydroSHEDS database to convert runoff estimates into streamflow. The GEM-based 50 km runoff estimates were previously validated using observations in HYDAT (Environment and Climate Change Canada, 2010), a database of streamflow data derived from WSC measurements, and the downscaled 5 km discharge estimates agreed well with the flow data from the earlier HKE database produced by Jenkinson and Bomhof (2014). The temporal resolution between these two datasets was reconciled partially by using FDCs and representing the flow statistically rather than using daily measurements or estimates. The flow duration curves produced by Jenkinson and Bomhof (Bomhof, 2014) were developed based on 889 hydrometric gauge stations with the following criteria: being unregulated, having more than ten years of data, and having recent (1995-2014) data. The flow duration curves generated from Teufel and Sushama (2022) are based on daily flow estimates from 1979-2016. Thus, the temporal discrepancies that exist between the two datasets, because of the difference in years of data used, are smoothed by the use of FDCs.

Figure 6-1 shows the spatial extent of the flow estimates derived from both studies (in the upper, left corner), highlighting the improved coverage for Arctic regions achieved

through Teufel and Sushama's (2022) contributions. Figure 6-2 illustrates the river flow data of the 50th percentile flow condition from Jenkinson and Bomhof (2014) in the south of Canada and the river flow data derived from Teufel and Sushama's (2022) estimates in the north of Canada. Each river in Figure 6-2 is represented with cross sectional averages in flow, depth, width, velocity, and power at 100 m, 200 m, or 400 m intervals, depending on the size of the river. For example, rivers shown in red in Figure 6-2 would have the larger measurement interval spacing of 400 m, and rivers shown in green in Figure 6-2 would have smaller measurement interval spacing of 100 m. Further information on the cross-section interval spacing in this dataset are included in Table 6-3. Only rivers with a 0.01% flow exceeding 100 m³/s were included in the new HKE database. With this criterion, this excluded rivers that were never expected to exceed 100 m³/s at any point in their hydrological cycle, such as creeks, irrigation streams, and minor tributaries, which were deemed unlikely to provide viable conditions for HKE development. The median 50th percentile flow for rivers with a 0.01% flow exceedance between 105-100 m³/s is 3.5 m³/s (IQR: 2.3-5.3 m³/s), indicating that rivers with flow less than this criterion would indeed not support large- to medium-scale HKE development. Validation metrics of the flow data, presented in Section 6.3.3.1, confirm the robustness of these estimates for use in HKE resource assessments.

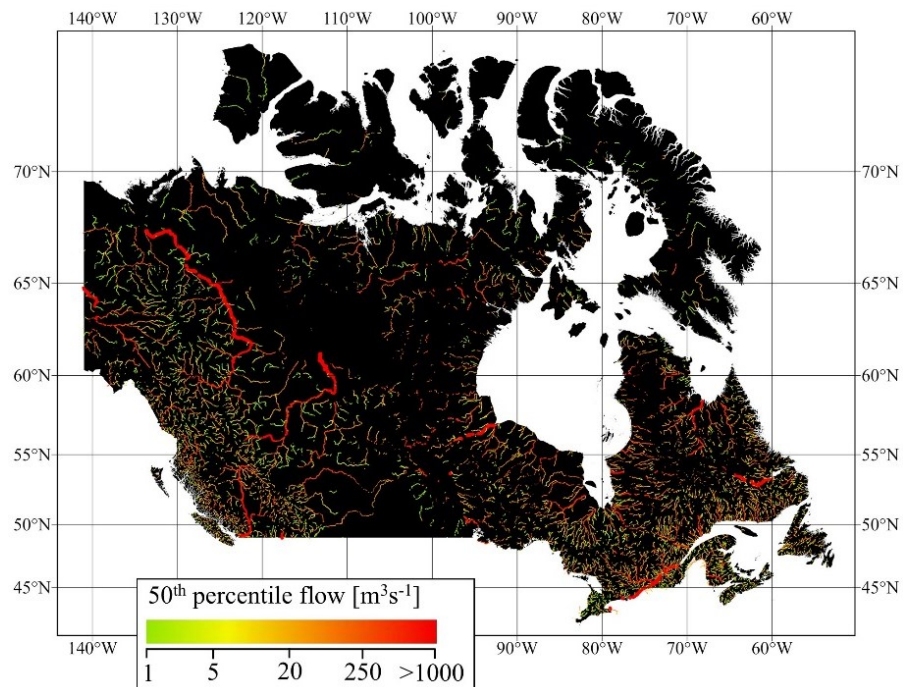


Figure 6-2: Flow estimates from Jenkinson and Bomhof (2014) and Teufel and Sushama (2022).

The flow estimates from Jenkinson and Bomhof (2014) and Teufel and Sushama (2022) were integrated into a national framework using the National Hydro Network

(NHN) for Canada. This ensured database spatial uniformity by utilizing consistent river identifiers and attributes across regions. The integration process involved appending flow estimates to the HKE database framework through proximity-based spatial matching. However, spatial discrepancies arose in some areas, with flow estimates from Jenkinson and Bomhof (2014) occasionally misaligned by more than a kilometer due to their reliance on the now superannuated Atlas of Canada – Drainage Network (Natural Resources Canada, 2008). These discrepancies were particularly problematic near river confluences, where accurately assigning flow estimates to the correct river branch often required manual corrections. To address this issue and avoid potential errors, data points near river confluences or areas where rivers were within 1500 meters of one another were removed from the dataset. This step ensured higher reliability and consistency in the database, though it limited coverage in certain complex river network areas. While alternative approaches such as flow apportionment could be used to preserve data in confluence zones, such methods require high-resolution flow routing data or channel geometry, which is not consistently available across Canada. Future work could explore such techniques to improve data retention in complex river networks. If HKE estimates are required at a confluence, estimates downstream or upstream of the area can be used to derive estimates at the confluence if the flow routing is taken into consideration and the river width measurement is adjusted.

6.2.3 River Depth Calculations

Depth estimates were derived using downstream hydraulic geometry (DHG) relationships, as developed by Jenkinson and Bomhof (2014). These regression-based relationships were formulated using cross-sectional survey data from the Water Survey of Canada Measurement Database (WSC-MD), which records channel geometry at various flow events across Canadian hydrometric gauge stations. DHG relationships typically represent channel-forming or bankfull flow conditions, capturing how channel geometry changes along a river reach (Leopold and Maddock, 1953). Bankfull flow refers to the maximum flow a channel can contain without overtopping into the surrounding floodplain (Copeland et al., 2000).

Jenkinson and Bomhof (2014) applied the principles of at-a-station hydraulic geometry to understand how the wetted channel geometry was influenced by flow conditions at surveyed sites. They then used this information to produce a range of DHG relationships, representative of different flow conditions. This approach allowed Jenkinson and Bomhof (2014) to estimate channel geometry across the full range of flow conditions represented in the FDC (see Table 6-2). The mathematical framework for these relationships is provided in Equations 6-4 to 6-9 below.

$$[6-4] \quad w = aQ^b$$

$$[6-5] \quad d = cQ^f$$

$$[6-6] \quad v = kQ^m$$

In addition, continuity was respected:

$$[6-7] \quad Q = wdv = aQ^b \times cQ^f \times kQ^m$$

and:

$$[6-8] \quad b + f + m = 1$$

$$[6-9] \quad a \times c \times k = 1$$

Where a, b, c, f, k , and m are variables optimized to fit the measured hydrometric data. The values of c and f determined by Jenkinson and Bomhof (2014), used in this study to estimate river depth, are listed in Table 6-2.

Table 6-2: Flow exceedance percentage, DHG depth constant (c), and DHG depth coefficient (f) from Jenkinson and Bomhof (2014).

Point on FDC	Flow Exceedance %	c	f
1	0.01	0.331	0.356
2	0.1	0.330	0.351
3	0.5	0.329	0.346
4	1	0.328	0.344
5	5	0.314	0.342
6	10	0.306	0.342
7	20	0.294	0.341
8	30	0.282	0.345
9	40	0.274	0.346
10	50	0.262	0.354
11	60	0.254	0.359
12	70	0.244	0.369
13	80	0.242	0.369
14	90	0.245	0.352
15	95	0.236	0.371
16	99	0.230	0.373
17	99.99	0.225	0.368

Figure 6-3 illustrates the depth estimates derived from these DHG relationships for the 50th percentile flow condition. Because the estimates of depth are derived from empirical relationships based on the river flow, the trend of depth in rivers across Canada shown in Figure 6-3 is similar to the trend in river flow in Figure 6-2. This similarity in depth and flow trends does not take into account unique geographical features like fault lines, bedrock outcrops, or human interventions like weirs or dams that would negate this depth-flow relationship. This is especially true considering that the hydraulic geometry relationships illustrated in Table 6-2 were developed from hydrometric gauge stations on unregulated rivers (Bomhof, 2014). Validation metrics of the depth data are presented in Section 6.3.3.1.

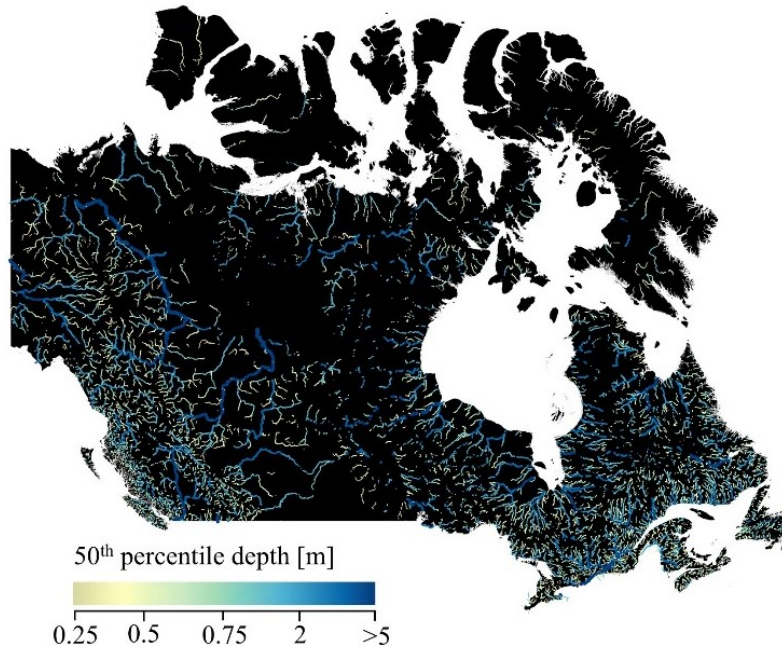


Figure 6-3: Depth estimates using the hydraulic geometry relationships from Jenkinson and Bomhof (2014) applied to the hydrokinetic energy database framework.

6.2.4 River Width Measurements

With improvements in satellite imagery and image-based data across Canada, as well as improved techniques for channel width and edge detection (Allen and Pavelsky, 2018; Yamazaki et al., 2014), river width estimation has become significantly more accurate and consistent. These advancements leverage the broader spatial coverage and reliability of remotely sensed data, addressing limitations of traditional field measurements.

To account for flow variance and improve HKE estimates, river widths were measured during multiple flow conditions at each cross-section. Using remotely sensed data, river cross-sections were analyzed every 100 m along the river centerline, enabling a detailed and dynamic representation of river geometry. This approach ensured that variations in channel width due to changing flow conditions were captured and integrated into the energy assessment framework.

6.2.4.1 *Data Sources for River Width Measurements*

The two primary data sources for extracting river widths were Sentinel-2 Multispectral Instrument (S2MSI) satellite imagery and the National Hydro Network (NHN) polygons for Canada.

Sentinel-2 Multispectral Satellite Imagery

S2MSI imagery was selected for its high revisit frequency (5 days between the S2A and S2B satellites) and moderate spectral resolution (ESA, TAS Team, 2021),

making it well-suited for surface water detection across large areas. A comparison between the accuracy of surface water maps derived from S2MSI imagery and Sentinel-1 SAR imagery was performed across four geographically diverse locations in Canada in two different seasonal conditions (eight total images) (Kirby et al., 2024c). This analysis found S2MSI to produce significantly higher accuracy maps across all images compared to SAR, although the analysis did not compare this to fused optical/SAR images which may produce more accurate results. S2MSI has been operating and collecting Earth observation data since 2015. From March 2018 onward, the data from S2MSI is available in bottom of atmosphere (BOA) level processing (Level 2A in S2MSI), and data collected before March 2018 must be pre-processed from top of atmospheric (TOA) level (Level 1C in S2MSI) to BOA level. This pre-processing is completed to remove or reduce atmospheric-based perturbations and signal scattering from atmospheric gases and particles. This is particularly important in the visible to near infrared (NIR) bands of optical imagery (Nazeer et al., 2021). Level 1C images can be atmospherically corrected to level 2A using the Sen2cor tool (Main-Knorn et al., 2017) in the SNAP application or similar.

S2MSI imagery offers optical resolutions of 10 m for red, green, blue, and NIR bands, 20 m for six intermediate bands, and 60 m for three atmospheric correction bands (ESA, TAS Team, 2021). However, the signal cannot penetrate cloud cover, nor can it distinguish water pixels from snow or ice in certain conditions, limiting its use during cloudy days, at night, or in regions with persistent winter cover. To address these limitations, imagery was filtered based on criteria such as cloud cover and seasonal conditions to ensure quality for surface water mapping. To minimize errors, pixels with potential cloud or shadow interference were excluded using the Scene Classification Map layer in S2MSI imagery. Pixels classified as a value of 0 (no data), 1 (saturated or defective), 3 (cloud shadows), 8 (cloud medium probability), 9 (cloud high probability), 10 (thin cirrus), and 11 (snow) were removed. Additionally, S2MSI tiles with more than 20% cloud cover or 0.1% ice/snow cover were excluded to prevent misclassification of ice and snow as water.

When S2MSI imagery was unavailable, NHN polygons were used as a complementary data source to maintain spatial uniformity in river width estimation. The combined use of S2MSI imagery and NHN polygons ensured comprehensive and consistent mapping of river widths across Canada.

National Hydro Network

The NHN is a geospatial framework of inland surface waters, including water polygons and centerlines, with a maximum 1:50,000 scale developed under the GeoBase Surface Water Program (Natural Resources Canada, 2019). Covering the far north of Canada – an area of significant interest for HKE estimation – the NHN provides a consistent national framework for waterbody mapping. However, the dataset has

limitations. The databases used to create the NHN polygons are not identified in its metadata. Therefore, the NHN geospatial data products cannot be reliably linked to specific dates. This uncertainty extends to the flow stage of the water polygons, reducing the applicability of the dataset for dynamic flow condition analyses. Additionally, waterbody locations in some regions have been observed to migrate from those shown in the NHN, potentially affecting accuracy in highly dynamic environments.

The NHN also includes watercourse centerlines derived from the waterbody polygons. These centerlines, which feature standardized ID attributes, served as the national framework for this study. They were used to calculate river widths instead of deriving new centerlines from S2MSI surface water maps, as demonstrated by Allen and Pavelsky (2018) and available via cloud-based processing (Yang et al., 2020). Although S2MSI-derived centerlines may offer higher resolution in specific areas, the use of NHN centerlines significantly reduced computational demand and ensured uniformity across the national dataset. This approach was particularly valuable for achieving consistent HKE estimates across Canada's vast and diverse river networks.

6.2.4.2 *Cloud Processing of Satellite Imagery*

To capture seasonal and inter-annual variability in river width, twenty-four surface water maps were generated for the open water months in Canada (May to October) during the years 2019 to 2022. These maps were created using S2MSI imagery processed in the cloud using Google Earth Engine (GEE) to improve image processing efficiency and reduce data storage requirements. The spectral index Automated Water Extraction Index, No Shadow (AWEI_NSH) was applied with a global -0.3 threshold to classify image pixels into water or non-water classes. This spectral index was selected for its superior performance in detecting water in the presence of reflective infrastructure and shadows, as well as its robustness across diverse geographic locations (Kirby et al., 2024a). The equation and multispectral bands to calculate the AWEI_NSH are shown below.

$$[6-10] \text{ AWEI}_{NSH} = 4 \times (\rho_{green} - \rho_{SWIR1}) - (0.25 \times \rho_{NIR} + 2.75 \times \rho_{SWIR2})$$

Where:

- ρ_{green} = reflectance value of the green band [-],
- ρ_{SWIR1} = reflectance value of the first short wave infrared (SWIR) band [-],
- ρ_{NIR} = reflectance value of the near infrared (NIR) band [-], and
- ρ_{SWIR2} = reflectance value of the second short wave infrared (SWIR) band [-].

A sensitivity analysis of the threshold for AWEI_NSH revealed that lower thresholds (e.g., -0.1 to -0.4) were most optimal for the AWEI_NSH spectral index (Kirby et al., 2024a). This sensitivity analysis was performed across four geographically diverse locations in Canada, and the results are available in the supplementary material of Kirby, et al. (Kirby et al., 2024a). This study found that a lower threshold of -0.3 was more likely

to properly classify shoreline pixels, especially in images with reflective objects. Figure 6-4 provides an example of surface water maps derived for the same location on different dates, illustrating the consistency of the AWEI_NSH index in detecting water under varying conditions. The automated threshold selection algorithm developed by Otsu (1979) was also tested in the sensitivity analysis but was found to underestimate the optimal threshold for AWEI_NSH, further supporting the manual choice of -0.3 (Kirby et al., 2024a).

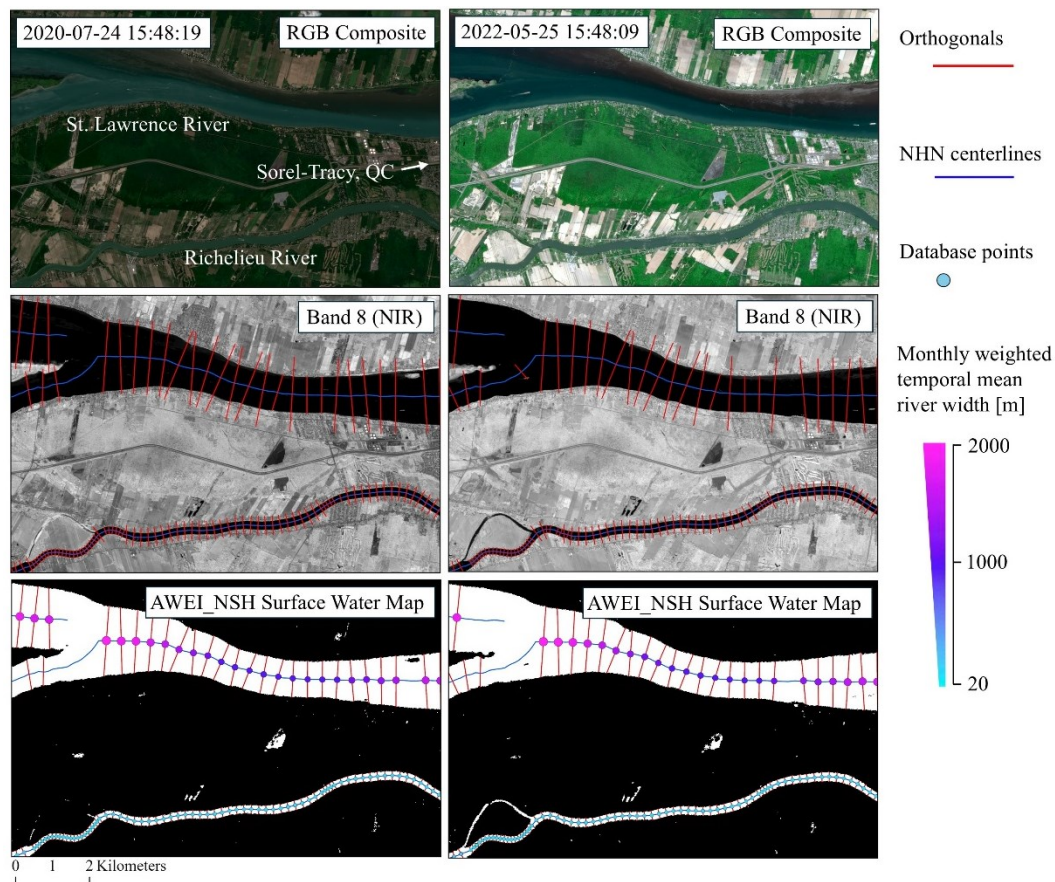


Figure 6-4: Illustration of NHN centerline and orthogonals used to derive width estimates from surface water maps on two different dates (July 24, 2020 and May 25, 2022).

6.2.4.3 *Deriving River Width Measurements from Surface Water Maps*

The first step in extracting river widths from the cloud-processed surface water maps was to convert the water extents into polygons. This procedure, along with all subsequent GIS processes, was completed using Model Builder in ArcGIS Pro Version 3.03. The NHN centerlines served as the framework for the database, with river widths measured at uniform spacing along the centerline, as shown in Figure 6-4. Figure 6-4 also illustrates some of the quality checks performed to reduce errors in the river width measurement procedures. In the lower left image, an orthogonal was not created on the

St. Lawrence River where a small island appeared in lower flow conditions. Areas where orthogonals crossed water boundaries more than two times were removed from the dataset to avoid under-estimating the width at these locations which would cause over-estimation of HKE. Additionally, comparing the middle right and lower right images in Figure 6-4, a small, erroneous orthogonal was removed that met the criteria of crossing a waterbody twice due to the small island in the St. Lawrence River. This orthogonal was removed using a check against the NHN-derived river widths, as satellite-derived river widths needed to be within $\pm 50\%$ of the NHN-derived widths as an additional quality check. This quality check may have removed some width measurements in very high and low flow conditions.

To measure river widths, perpendicular lines (herein referred to as orthogonals) were generated from the centerline at varying intervals based on river width. These orthogonal were clipped to the banks of the river polygons to determine cross-sectional widths. The spacing of these cross-sections was adjusted, as detailed in Table 6-3, to balance computational efficiency and measurement resolution. Refining measurements further was not observed to improve the identification of localized high energy sites. For instance, a 1 km wide river typically exhibits minimal morphological changes within 400 m, making additional measurements unnecessary for identifying significant velocity or power variations. This tiered approach to the measurement spacing is illustrated in Figure 6-4 where large rivers such as the St. Lawrence were sampled less frequently than smaller rivers such as the Richelieu River.

Table 6-3: River width and cross-section measurement spacing in the hydrokinetic energy database.

River width [m]	Cross-sectional spacing [m]
< 200	100
200 - 500	200
500 - 3000	400

The resulting width measurements were appended to the HKE database as the width at each location for a specific month and year, capturing temporal variability critical for HKE assessments. NHN centerlines were used instead of generating centerlines from surface water to maintain a uniform national framework. However, as previously noted, the NHN centerlines did not always reflect the current location of rivers in areas where river migration had occurred.

To address this limitation, a shared attribute ID between NHN centerline points and the orthogonals used for width measurements ensured accurate database integration. This approach allowed width measurements from orthogonals extending beyond the NHN centerline to be appended correctly to the database. Monthly mean widths and weighted

temporal means were then calculated using the equations provided below, summarizing seasonal and annual variations in river geometry.

$$[6-11] \mu_j = \frac{\sum_{i=1}^h (w_{j,i})}{h}$$

$$[6-12] \mu = \frac{\sum_{j=May\ to\ October} (\mu_j)}{g}$$

Where:

- i = numbered satellite-based width for each month (maximum 4 measurements from 2019 to 2022) [-]
- j = month of open water imagery (May, June, July, August, September, or October) [-]
- h = number of satellite-based width measurements for an open water month [-]
- μ_j = monthly mean width [m]
- g = number of monthly mean widths (maximum 6 means from months May to October) [-]
- μ = monthly weighted temporal mean width [m]

In addition to the individual width measurements, the monthly means, and the monthly weighted temporal means, the maximum and minimum width measurements were recorded in the database.

6.2.5 Velocity, Power, and Annual Energy Production Calculations

Velocity was calculated using the flow continuity equation, as illustrated in Equation 6-2. At each point on the FDC (see Table 6-2), velocity was determined based on the flow, width, and depth at that flow exceedance, resulting in a VDC. Because width measurements were derived from the 24 surface water maps rather than the 17-point FDC, specific adjustments were made to match flow exceedance conditions. The monthly weighted temporal mean widths were applied to flow exceedances between 20% and 70% (points 7 to 12). The maximum extracted width was used for high flow exceedances (0.01% to 10%; points 1 to 6), while the minimum extracted width was applied to low flow exceedances (80% to 99.99%; points 13 to 17). This method ensured realistic velocity estimates, avoiding overestimation at high flows, which heavily influence the final AEP value and underestimation at low flows (Kirby et al., 2023b).

At each velocity on the VDC, the available theoretical power was calculated using Equation 6-1. These calculations assumed a turbine with a swept area of 1 m², providing baseline power values that can be scaled up or down based on turbine size. For example, doubling the swept area to 2 m² would double the power available to the turbine. This flexibility ensures the results are applicable to a variety of turbine designs and installations. Turbine efficiency and other technical and practical limitations were not accounted for in these power estimates.

The resulting Power Duration Curves (PDCs) at each cross-section were interpolated using Equation 6-3 to estimate the AEP. AEP values were reported in units of megawatt-hours per year (MWh/year) to align with industry standards, rather than SI units of $\text{kg}\cdot\text{m}^2\cdot\text{s}^{-2}$. This conversion provides a more practical metric for energy developers and stakeholders.

6.2.6 Database Evaluation

To evaluate the accuracy of the HKE database, both input variables (depth, width, and flow) and output variables (velocity, power, and AEP) were validated. This process aimed to quantify how input errors influenced final estimates and to identify potential biases in the methodology. Table 6-4 summarizes the validation approaches, data sources, and methods used for this analysis.

Table 6-4: Validation data and approaches.

River Characteristic Validated	Validation Approach	Measurement Source(s)
Depth (d)	Comparison to 156 measurements of river depth across 35 spatially diverse river sections	Field measurements & WSC measurements
Width (w)	Comparison to 156 measurements of river depth across 35 spatially diverse river sections	Field measurements & WSC measurements
Flow (Q)	Comparison to 459 measurements of river flow across 35 spatially diverse river sections	Field measurements & WSC measurements
Velocity (v)	Comparison to 156 measurements of river velocity across 35 spatially diverse river sections, and comparison to 27 modelled values of velocity at 3 different river sections based on field data	Field measurements, WSC measurements, and hydrodynamic model from Kirby et al. (Kirby et al., 2023b, 2024b, 2025a)
Power (P_K)	Comparison to 27 modelled values of power at 3 different river sections based on field collected data	Hydrodynamic model from Kirby et al. (Kirby et al., 2023b, 2024b, 2025a)
AEP	Comparison to 3 modelled values of AEP at 3 different river sections based on field collected data	Hydrodynamic model from Kirby et al. (Kirby et al., 2023b, 2024b, 2025a)

The validation utilized a combination of datasets, including the Water Survey of Canada (WSC), field measurements, and hydrodynamic models. The WSC (Government of Canada, 2023) historical hydrometric data from 27 spatially diverse gauge stations were used to validate depth, width, flow, and velocity estimates. Multiple measurements across flow conditions resulted in comparison to 141 measurements of depth, width, flow, and velocity. The WSC data were accessed from https://wateroffice.ec.gc.ca/search/historical_e.html. An acoustic Doppler current profiler (ADCP) was used to collect field measurements from eight survey sites (15 additional data points from multiple flow conditions). This additional field survey data were used to

identify biases in WSC data. Finally, three hydrodynamic models, developed using TELEMAC-2D (Hervouet, 2007), provided simulations of velocity flow fields, power, and AEP based on field data and FDCs. These models at the Sylvia Grinnell River (Kirby et al., 2024b), the Riviere Rouge (Kirby et al., 2023b), and the Spanish River (Kirby et al., 2025a) in Canada followed the International Electrotechnical Commission's guidelines for river HKE assessments (IEC, 2019).

For depth, width, flow, and velocity, the following evaluation metrics were applied:

- Variance (R^2): Measures how well the estimates align with observed values.
- Bias (y-intercept): Indicates systematic over- or underestimation.
- Drift (slope): Evaluates proportional errors compared to the one-to-one relationship.
- Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE): Quantifies the magnitude of deviations.

For velocity, power, and AEP, validation focused on R^2 , bias, and drift, using results from three hydrokinetic studies at the Sylvia Grinnell River (Kirby et al., 2024b), the Riviere Rouge (Kirby et al., 2023b), and the Spanish River (Kirby et al., 2025a) based on field-collected data. These studies characterized power over a typical year, ensuring compliance with IEC guidelines.

The validation exercise was further divided into hydrometric gauge stations on regulated rivers and stations on non-regulated rivers to understand the impact of river regulation on the success of the estimation techniques. The distinction between regulated and non-regulated river sites was performed with a combination of WSC official labelling, the distance of the gauge station to the flow regulation device, and visual observation. Further, the impact of river regulation on flow was treated differently than the impact of river regulation on depth, width, and velocity. River regulation can affect the flow of the river many kilometers downstream of the regulation device. Thus, stations within 200km of a flow regulation device were defined to be “regulated” for the flow validation exercise. On the other hand, the impact of river regulation on depth, width, and velocity are relatively more localized, such as backwater and sediment transport effects. Stations within 10km of a flow regulation device and confirmed to be impacted by the presence of the flow regulation device (i.e., the shape, size, or movement of the river was impacted) were defined to be “regulated” for the depth, width, and velocity exercises.

6.3 Results and Discussion

6.3.1 National River Width Estimates

A total of 14,614,257 satellite-derived width measurements were collected at 1,325,261 river cross-sections. Where satellite-based widths were unavailable, NHN water polygon-derived widths were used at 178,985 cross-sections, ensuring

comprehensive coverage. With 288,000 km of river centerlines in the database, the average distance between width measurements and HKE estimates was 190 m. Validation metrics showed very good agreement between field measured widths and the widths measured in this study (MAPE of 17.0%). These validation metrics are presented in Section 6.3.3.1.

Monthly weighted temporal mean widths, calculated using Equations 6-11 and 6-12, and NHN-derived widths are presented Figure 6-5a. The widest rivers detected included the Mackenzie, Slave, St. Lawrence, Ottawa, Saguenay, and Manicouagan Rivers. Accurate representation of these river widths is crucial for HKE estimation, as under-estimation of river widths can result in significant overestimation of HKE potential. Particularly, rivers within topographic irregularities (e.g., canyons or fault-lines) or subject to human regulation (e.g., dams and power generating stations) such as the Saguenay, Manicouagan, St. Lawrence, and Ottawa Rivers have reduced velocity, limiting hydrokinetic feasibility.

Figure 6-5b illustrates the number of satellite-based width measurements extracted by month and year. The lowest measurement counts occurred in May and October, coinciding with snow and ice cover in northern and mountainous regions, while August recorded the highest number of measurements due to cloud-free and snow-free conditions. Among the evaluated years, 2021 had the highest measurement count, surpassing 2022 by nearly 500,000 measurements. Similar measurement counts were observed in 2019 and 2020.

Analysis across Canada's 11 major drainage basins (Figure 6-5c(i)) revealed regional variability in satellite-based measurements. The regions with the lowest average measurements per cross-section included the Maritimes (6.5), Mississippi (6.6), Yukon (7.8), and Pacific (8.3) regions, primarily due to narrower river sizes and higher prevalence of cloud cover. In contrast, the Albany region recorded the highest average measurements per cross-section (14.2), attributed to its wider rivers (90 m on average) and fewer snow- or cloud-covered images during spring and autumn months (Figure 6-5c(ii)).

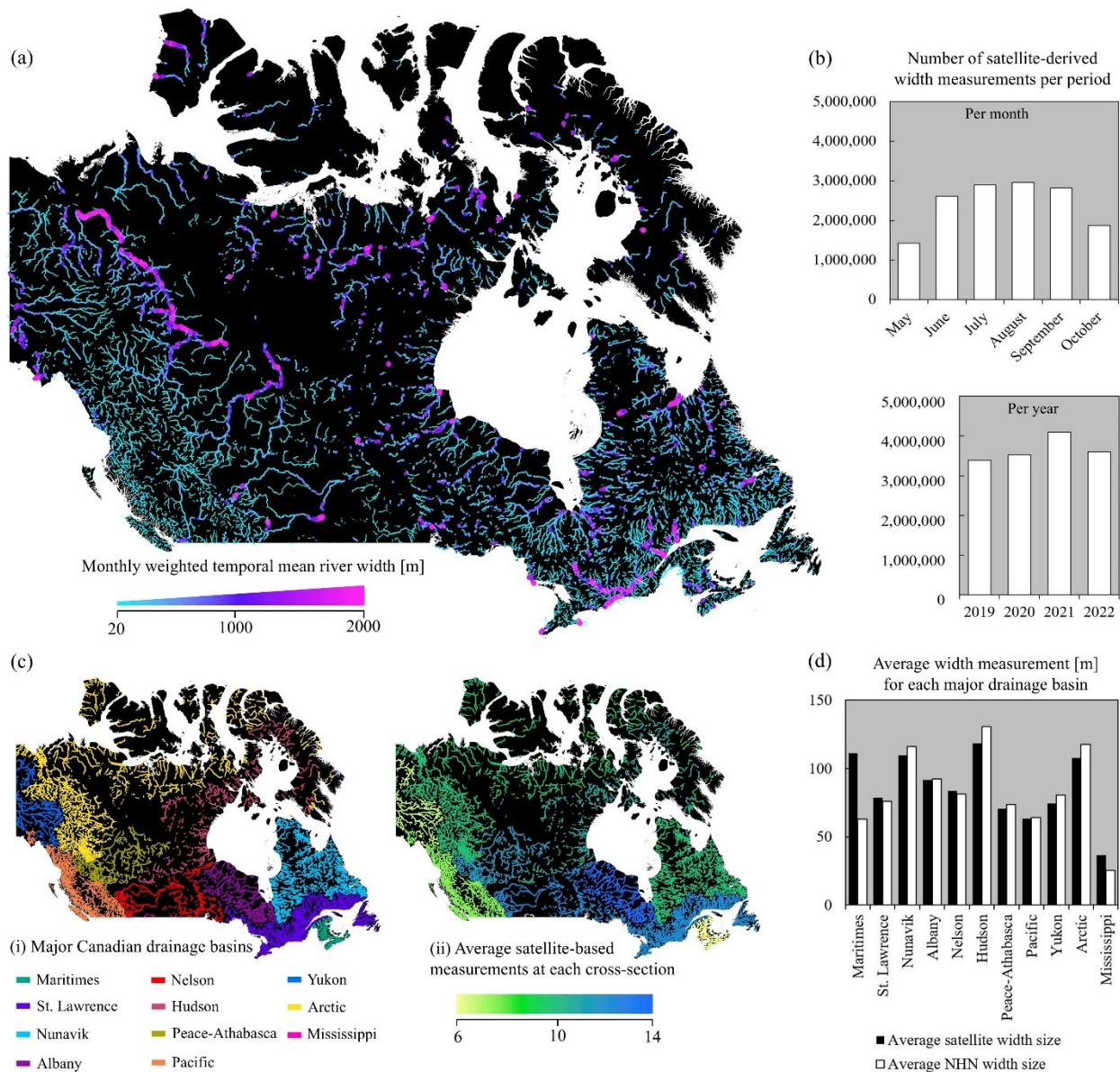


Figure 6-5: (a) Spatial distribution of river width estimates across Canada, derived from satellite imagery and NHN polygons. (b) Temporal variability in the number of satellite-based width measurements, presented by month and year. (c) (i) The 11 major Canadian drainage basins as defined by the NHN, and (ii) the average number of satellite-based width measurements at each cross-section. (d) Mean river width measurements, including satellite-derived and NHN-derived estimates, across the 11 major drainage basins. These subplots illustrate regional and temporal trends in river width measurements, highlighting challenges such as cloud cover and snow/ice conditions, and the importance of consistent width measurements for HKE assessments

Atmospheric disturbances, such as clouds, and snow/ice cover affected the use of S2MSI satellite imagery, resulting in gaps in the river width measurements. Over the 30

image capture periods used in this study (May to October months and years 2018 to 2022), some locations did not have sufficiently cloud-free or snow/ice-free imagery available. For example, the west coast of Canada is particularly rainy and would have fewer cloud-free days. Additionally, Arctic Canada does not become snow/ice free until mid- to late-July. Thus, image tiles in Arctic Canada locations cannot be used in May and June because of the resulting inaccuracies. As a result, measurements were not continuous every 100 m or at the frequency presented in Table 6-3. Including such pixels with atmospheric disturbances or ice/snow cover would have inflated river width measurements and introduced biases into the HKE resource estimates.

The impact of these exclusions is shown in Figure 6-6a, which shows that, out of a maximum possible 24 measurements from 24 surface water maps, a maximum of 18 width measurements were extracted in some regions. Mountainous areas in Western Canada and Arctic regions exhibited the fewest measurements due to persistent cloud cover, glacier, and snow/ice conditions. These limitations highlight the challenges of using optical satellite imagery in regions with adverse atmospheric conditions. Those regions shown in Figure 6-6a with fewer width measurements contain increased uncertainty in the width, velocity, and power estimates compared to locations that had more measurements available to derive mean, maximum, and minimum width measurements. This is especially true for river locations where only one width measurement could be captured from satellite imagery.

Despite these limitations, the approach captured significant changes in river width (Figure 6-6b). Larger rivers in low to moderately sloped areas, such as the Mackenzie, Slave, and Albany Rivers, exhibited greater variability in width. This variability must be incorporated into AEP estimates in order to ensure an accurate and robust assessment of available power resources. Measurements at flow splits (e.g., at anabranches or braided channels) focused on the primary channel, as defined by NHN, due to challenges in estimating flow ratios across branches without field data. Excluding velocity, power, and AEP estimates at these locations prevents inaccuracies, ensuring the database remains reliable for developers and communities.

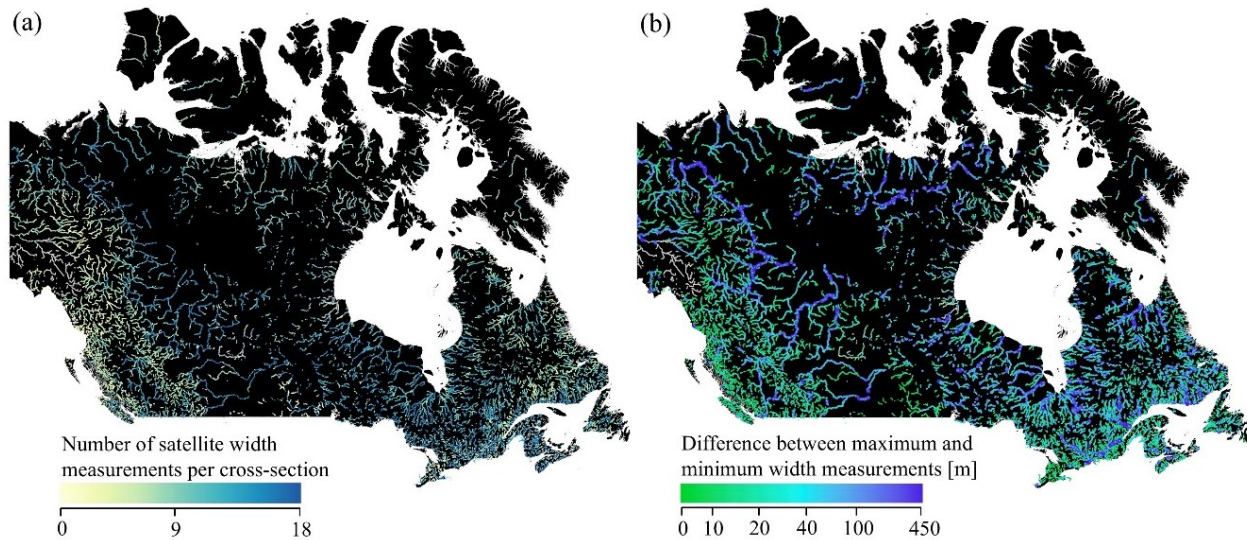


Figure 6-6: (a) The number of satellite-derived river width measurements extracted per cross-section, illustrating spatial coverage across Canadian rivers. (b) The range of width measurements for each river cross-section, presented as the difference between the maximum and minimum satellite-derived widths. These metrics highlight regional variability in measurement availability and changes in river width over time, providing essential data for HKE resource assessments.

6.3.2 The National River Hydrokinetic Energy Database and Regional Trends

The newly developed Canadian River Hydrokinetic Energy (CRHE) database identifies high-potential hydrokinetic hotspots across Canada. With cross-sectional estimates available every 190 m on average (every 100 m for smaller rivers and every 400 m for larger rivers), localized high-velocity and high-power conditions can be pinpointed. A demonstration of the database and two localized high-energy cross-sections is presented in Figure 6-7a. Validation of the CRHE database velocity estimates against both WSC-MD field data and hydrodynamic model simulations are presented in Section 6.3.3. Validation of the CRHE database power and AEP estimates against hydrodynamic model simulations is presented in Section 6.3.3.2. As illustrated in Figure 6-7a, remote communities like Kuujjuarapik, QC can use the database to identify nearby locations of high HKE resource for good electricity development potential.

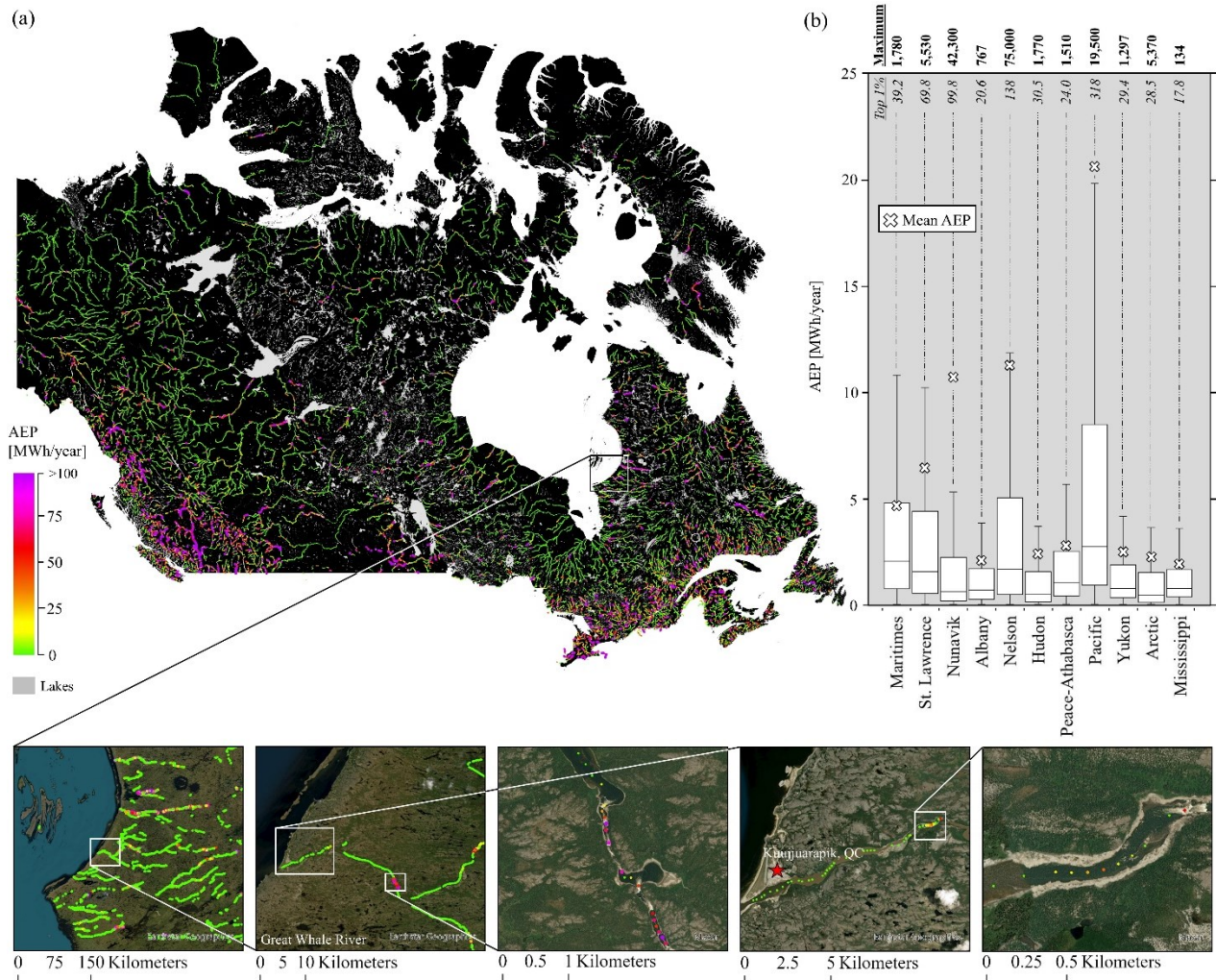


Figure 6-7: (a) National hydrokinetic energy estimates and two localized high energy areas identified near Kuujuaupik, QC on the Great Whale River. (b) Box and whisker plots of AEP for each of the 11 major Canadian drainage basins (see Figure 6-5c(i) for location of basins).

The database predicts the highest HKE potential in areas with steep topography and high slopes, particularly in British Columbia, Eastern Ontario, Quebec, and Labrador. These areas are dominated by bedrock-controlled river systems with geomorphological features such as narrow valleys, lateral constrictions, and steep channel gradients (Ferguson and Rennie, 2017), all of which contribute to increased flow velocities and greater HKE potential. For example, the Fraser River in British Columbia's Fraser Canyon exhibits severe lateral constriction and confined channel morphology (Rennie et al., 2018), resulting in the highest HKE potential observed in the dataset (Venditti et al., 2014).

Across the Canadian drainage basins, the Pacific basin ranked highest in both mean and median annual energy production (AEP), consistent with its mountainous terrain, steep river profiles, and high precipitation runoff. In contrast, the Mississippi basin,

dominated by broad, low-gradient alluvial plains and lower runoff due to the combination of multiple hydro-geomorphological features (e.g., prairie potholes, high infiltration, etc.) exhibited the lowest mean AEP. These varied hydro-geomorphological features drive localized and regionalized variability in HKE potential. Figure 6-7b compares the mean, median, and standard deviation AEP in box and whisker plots for the major Canadian drainage basins, highlighting differences in HKE potential across Canada (whiskers represent 1.5 IQR).. At the top of Figure 6-7b the maximum and top 1% AEP values are listed for each Canadian drainage basin.

As illustrated in Figure 6-7b, most river cross sections were estimated to have low AEP (0 to 5 MWh/year), but a small number of cross sections in each region had very high AEP, causing the mean AEP to be consistently and substantially higher than the median AEP. Both the Nunavik and Pacific regions, and St. Lawrence region to less of an extent, had the largest differences between the mean and median AEPs and had some of the largest maximum and top 1% AEPs. Upon visually inspecting these very high AEP locations, the rivers with such estimates were constrained within canyon walls with large amounts of white water and/or rapids. This large difference between mean and median AEP was also present in the Nelson region. However, this skew is somewhat due to flow estimate errors in the prairie regions where flow is often overestimated by hydrological models due to prairie potholes and complex cold region hydrology (Ahmed et al., 2023). This error is further evaluated and discussed in Section 6.3.3.1. The skew in the Nelson region is also due to the highly regulated nature of rivers in the Nelson basin. The river flow in some locations is diverted into multiple channels, and this alteration was not able to be captured in the hydrological or regression modelling. Thus, estimates of AEP are inflated in these highly regulated channels.

6.3.3 Evaluation of Estimates

6.3.3.1 *Evaluation using Water Survey of Canada Data: Flow, Depth, Width, and Velocity*

The input estimates for flow (from Jenkinson and Bomhof (2014) and Teufel and Sushama (2022)), depth (derived from hydraulic geometry relationships in Jenkinson and Bomhof (2014)), and width (from S2MSI imagery) were validated against the Water Survey of Canada Measurement Database (WSC-MD). Field measurements of flow, depth, width, and velocity were collected with ADCP by WSC at 35 river locations under multiple flow conditions. Figure 6-8 shows the WSC gauge stations (“G”) and field measurement sites (“M”) used in the validation exercise, alongside the average flow and velocity at each location. These provide context for the range of comparisons conducted. Many of the validation river locations in Figure 6-8 included in this analysis are located on unregulated rivers (see Figure 6-9d), and some of these unregulated validation locations are located at rivers with unique morphological features. The Fraser River (validation locations M1, M2, and M3) is one such river that is located in a canyon that influences

flow patterns and the shape of the river. Additionally, highly regulated rivers are included in this analysis, such as the Rideau River (M6, M7, and M8) that are controlled through a series of weirs and dams. Including these cases in the validation exercise allows for analysis and discussion on the limitations of the methods and derived estimates from this study.

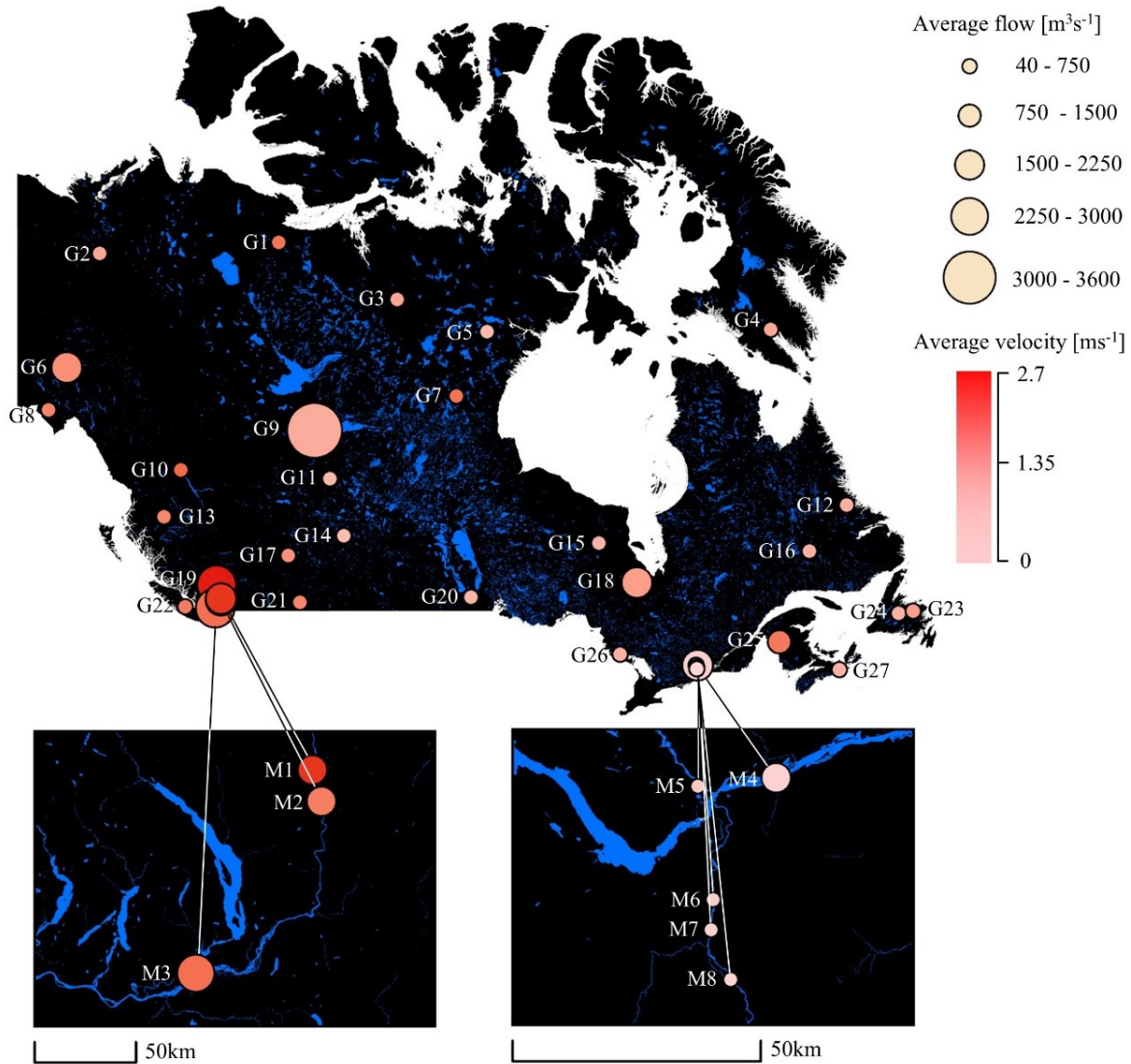


Figure 6-8: Hydrometric gauge (G) and measured (M) stations used for validation of velocity, width, depth, and flow estimates.

Illustrated in Figure 6-9c and Figure 6-10a, the estimates of river flow used in this work from Jenkinson and Bomhof (2014) and Teufel and Sushama (2022) were acceptable, but in general, river flow was overestimated. This was particularly the case for river flows higher than $2000 \text{ m}^3\text{s}^{-1}$ and for rivers located in the Prairie or Parkland regions of Canada (South Saskatchewan and South-west Manitoba in the Nelson basin, Figure 6-5c(i)). These areas are characterized by unique hydrology owing to the presence

of prairie potholes and complex cold region hydrology. Literature that has tested existing hydrological models in this region have shown that some models have difficulties in simulating streamflow over these drainage basins, even if the models performed well elsewhere and were well calibrated to observed streamflow (Ahmed et al., 2023). Application of hydrological models that are well-suited to the region of interest, rather than applying a global hydrological model, or calibrating hydrological parameters locally rather than globally may alleviate these errors associated with river flow. Additionally, newly developed algorithms that can be used to estimate river flow from remotely sensed data (Elmi et al., 2024; Gehring et al., 2022) may prove promising for improved flow estimates. The flow estimates were more accurate for regulated rivers, as shown in Figure 6-10a and Table 6-5. Figure 6-9d shows that rivers are more likely to be regulated in Southern Canada, where Canada is more urbanized compared to the north. Hydrological and hydrometric data is higher quality and in greater abundance in these urbanized locations. Thus, the models used to estimate river flow were likely better calibrated in these locations.

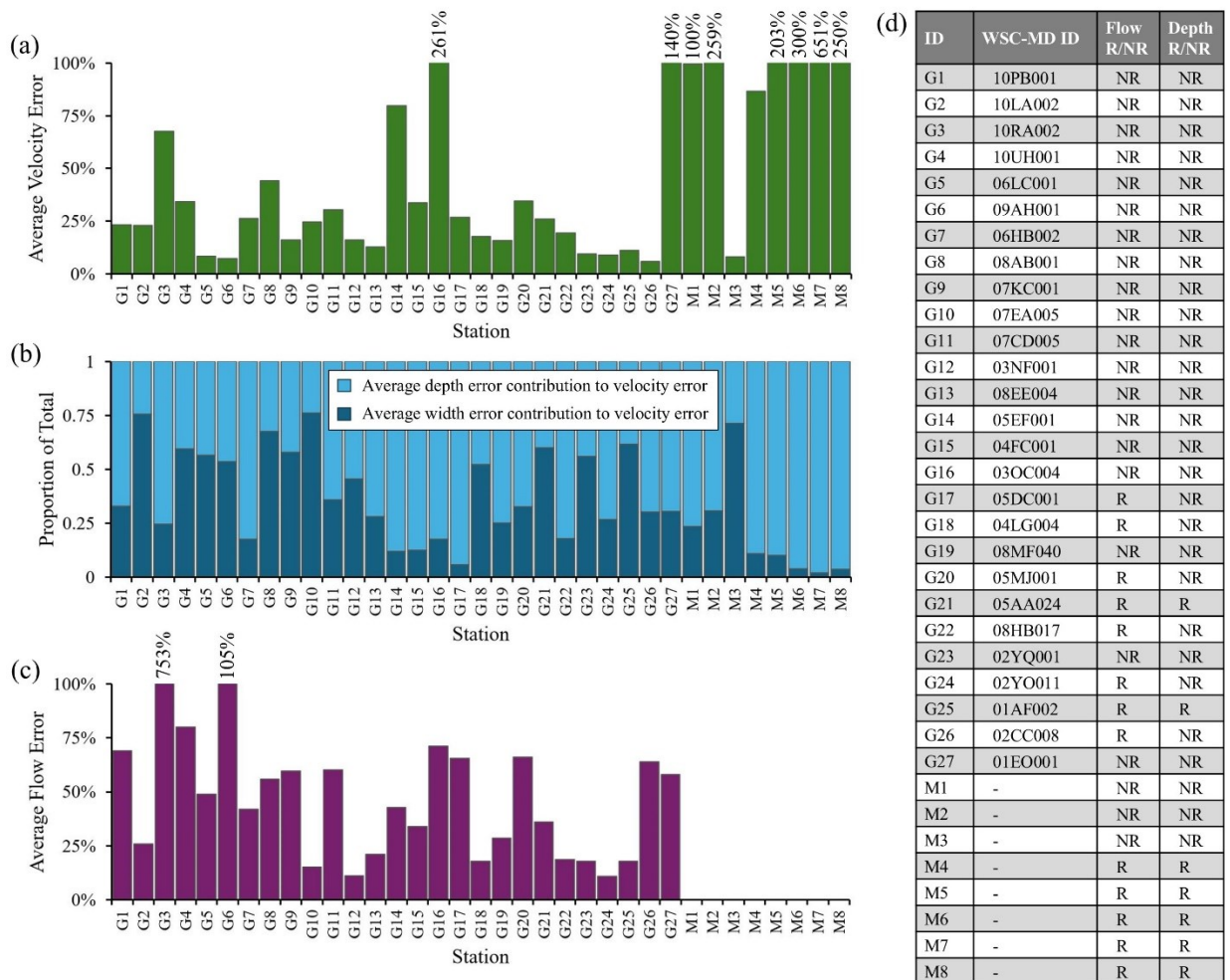


Figure 6-9: Validation results comparing hydrometric gauge measurements (G) or field measurements (M) to estimated values: (a) Average velocity error at each site, illustrating discrepancies in velocity estimates for hydrometric gauge stations and field sites; (b) Contribution of depth and width errors to velocity errors, with depth identified as the dominant source of error at most sites; (c) Average flow error, highlighting areas where flow estimates deviate significantly from measured values; (d) A list of the WSC hydrometric gauge stations (G) and ADCP measurements (M) used in the validation exercise along with if the river location is regulated (R) or non-regulated (NR). Flow has different R and NR distinctions from depth, width, and velocity. Flow validation data for field measurements (M1 to M8) are not available due to data limitations at these sites.

Figure 6-10b demonstrates that river depth was generally underestimated in the CRHE database, particularly at sites with unique natural or regulated conditions. At sites like M1 and M2 on the Fraser River, deep scour in the bedrock floor caused by canyon flow structures resulted in depths exceeding those predicted by hydraulic geometry relationships (Venditti et al., 2014). These cases highlight the limitations of applying simplified relationships to complex geomorphological settings. Additionally, sites such as M6, M7, and M8 on the Rideau River and M4 and M5 on the Ottawa and Gatineau Rivers, respectively, had artificially increased depths due to dam regulation for boat passage. Hydraulic geometry relationships were also unable to capture these effects. When removing these regulated rivers from the validation exercise and only including unregulated rivers, the depth estimates for unregulated rivers are shown to be slightly better than those for regulated rivers (see Figure 6-10b and Table 6-5). To improve depth estimates, other relevant characteristics that relate to river depth, such as landcover, slope, or surficial geology could be used to refine the hydraulic geometry relationships, as performed by Bomhof et al. (2015). Additionally, the recent increase in the availability of medium resolution remotely sensed water surface elevation data could be used to derive national or global estimates of river depth for rivers wider than 100 m from the Surface Water and Ocean Topography (SWOT) mission (Altenau et al., 2021) or from multi-source remotely sensed data (Tourian et al., 2017; Wu et al., 2023).

River widths extracted from S2MSI imagery agreed very well with field measurements (Figure 6-10c), with a slight bias toward overestimation due to the global -0.3 threshold used. While this threshold ensured waterbody continuity, it occasionally misclassified shoreline pixels containing more land than water as water, increasing width estimates. This slight bias had minimal impact on velocity estimates compared to depth errors. As shown in Figure 6-9a and Figure 6-9b, most validation sites with high velocity errors had a higher contribution of depth error to the velocity error. Thus, for improved estimates of velocity and HKE, it is recommended that efforts be placed into improving the estimates of river depth rather than river width. The river width measurements in the

database were not affected by the regulation or non-regulation of the river (see Figure 6-10c and Table 6-5).

Velocity estimates showed good agreement with measured values, with a slope near 1 and a y-intercept close to 0 (Figure 6-9a). However, an R^2 of 0.57 indicates significant variability, primarily due to errors in depth and flow inputs. Sites with high velocity errors, such as G16, G27, and field measurement sites, were largely influenced by depth underestimation (Figure 6-9b). However, with an average MAE of 0.37 m/s across all validation locations (Table 6-5), utilization of the average cross-sectional velocity from this database for site selection is still recommended, as it can still give developers and communities an idea of the resource magnitude at a candidate site in comparison to other candidate sites. For example, some turbines require a cut-in velocity of 1 m/s and have a cut-out velocity of 3.5 m/s (ORPC, 2023). The MAE of 0.37 m/s is well within this 2.5 m/s range of operable velocities. To improve velocity and HKE estimates, efforts should focus on refining depth and flow inputs through incorporating remote sensing data for depth and flow and application of regional hydrological models tailored to specific basins. The estimates of velocity did not seem to be affected by river regulation or non-regulation, as illustrated in Figure 6-10d and Table 6-5.

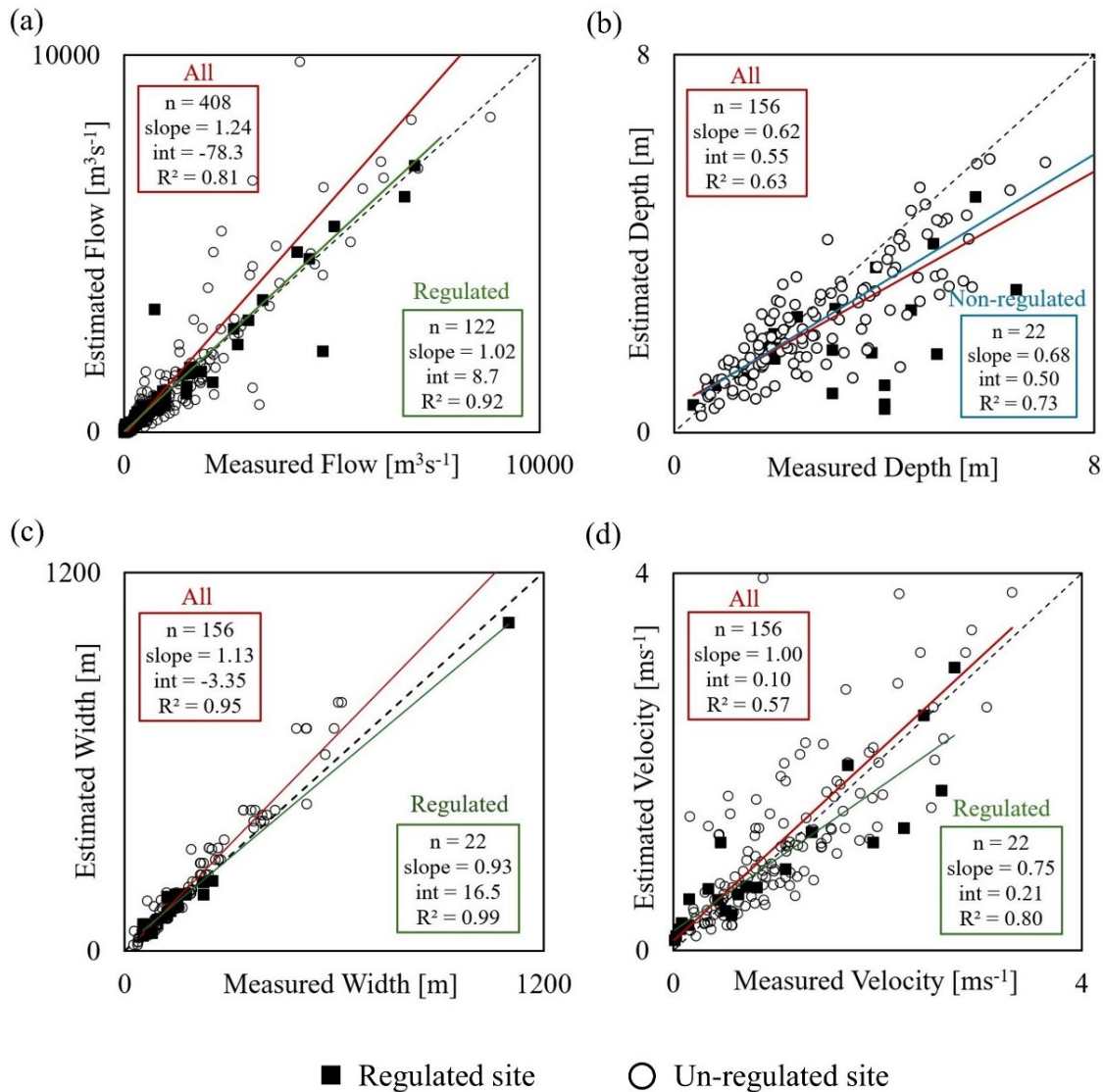


Figure 6-10: Validation results comparing hydrometric gauge measurements from the Water Survey of Canada to estimates of (a) flow, (b) depth, (c) width, and (d) velocity. The solid dark red lines represent the linear regression trends of all the validation points, the solid dark green lines represent the linear regression trends of the sub-set validation points (either regulated or non-regulated), and the hatched black lines indicate the ideal one-to-one relationship (perfect agreement).

Table 6-5: Validation metrics of using all gauge stations, only non-regulated river gauge stations, and only regulated river gauge stations.

River characteristic	Included gauge stations	MAE	MAPE [%]	RMSE
Flow [m^3s^{-1}]	All	264.4	58.8	977.7
	Non-regulated	317.3	71.5	1134.3
	Regulated	140.3	29.9	425.14
Depth [m]	All	1.01	27.6	2.19

	Non-regulated	0.97	25.9	2.25
	Regulated	1.29	37.7	1.81
Width [m]	All	28.8	17.5	47.6
	Non-regulated	30.2	17.2	50.2
	Regulated	20.4	19.1	26.5
Velocity [ms ⁻¹]	All	0.37	57.5	0.64
	Non-regulated	0.38	43.5	0.67
	Regulated	0.29	142.9	0.40

6.3.3.2 *Evaluation using Hydrodynamic Modelling: Velocity, Power, and AEP*

In addition to validating input and derived values against WSC and field data, velocity, power, and AEP estimates from the CRHE database were compared to the results of three hydrodynamic models for geographically diverse river reaches: the Spanish River (Kirby et al., 2025a), Rivière-Rouge (Kirby et al., 2023b), and Sylvia Grinnell River. The locations of these rivers are shown in Figure 6-11d.

The estimated values for velocity, power, and AEP in the Spanish River showed good agreement with modelled values, as illustrated in Figure 6-11a for velocity, Figure 6-11b for power, and Figure 6-11d for AEP. The regression slopes for velocity and power were close to one, indicating strong alignment with modelled data. While some positive bias was observed, the overall magnitude of the estimates was good. The estimated AEP was lower than the modelled AEP by 2.6 MWh/year (61%; Figure 6-11d). The percent difference in AEP is high for this site because of the low magnitude in AEP at this location, but the overall trend in AEP magnitude between the three validation locations (i.e., Spanish River being lowest, Sylvia Grinnell River being middle, and Rivière-Rouge being highest) demonstrates reliability of the dataset for HKE site identification before further resource characterization takes place.

For the Rivière-Rouge, velocity and power estimates were in good agreement with modelled values at lower flows, but underestimation occurred at higher flows (Figure 6-11c). The five lower flow conditions followed the one-to-one relationship well, while the two highest flow conditions deviated from the one-to-one relationship. This resulted in an overall underestimation in AEP of 14.3 MWh/year compared to the model (42%; Figure 6-11d). However, the discrepancy at higher flows may stem from limitations in the hydrodynamic model rather than the CRHE database. The model relies on an assumed downstream water elevation (Kirby et al., 2023b), which may overestimate velocity and power at high flows. Despite these differences, the overall trend of AEP estimation for the Rivière-Rouge aligns with the goal of the CRHE database to identify areas of high HKE potential.

For the Sylvia Grinnell River, velocity estimates were slightly underestimated at lower flows but aligned well at higher flows. This trend is shown in Figure 6-11b and Figure

6-11c, where power values also agreed at higher flows but deviated at lower flows. The discrepancy at low flows is likely due to differences in how winter months were represented in the flow duration curve (FDC). In the model validation data, the FDC included only open water months, while the CRHE data incorporated months with minimal or no flow due to river freezing. Despite this, both the modelled and CRHE database AEP calculations adjusted for these differences using a 6-month and 12-month period, respectively, in Equation 6-3. As a result, the estimated and modelled AEP values showed good agreement for the Sylvia Grinnell River with a difference of 3.7 MWh/year (22%; Figure 6-11d).

The validation results demonstrate the reliability of the CRHE database in estimating velocity, power, and AEP across diverse river systems. While discrepancies exist, particularly at extreme flow conditions or when river ice is present, these differences are often linked to limitations in the hydrodynamic models or variations in input data assumptions. As illustrated by the slopes of the linear relationships between power from hydrodynamic modelling and estimated power from this database (1.36 for Spanish River, 1.00 for Sylvia Grinnell River, and 0.27 for Rivière-Rouge; Figure 6-11b), realistic estimates of power at each flow exceedance are not achievable in this database. The database is not able to provide temporally high-resolution estimates of power across the FDC. However, the AEP values, integrated across the full flow duration curve, provide a robust basis for comparing and ranking candidate sites in terms of relative resource magnitude (Figure 6-11d). Future improvements could include refining the representation of winter flow conditions in the FDC for regions with significant freezing and incorporating region-specific hydrodynamic parameters to improve alignment with local conditions.

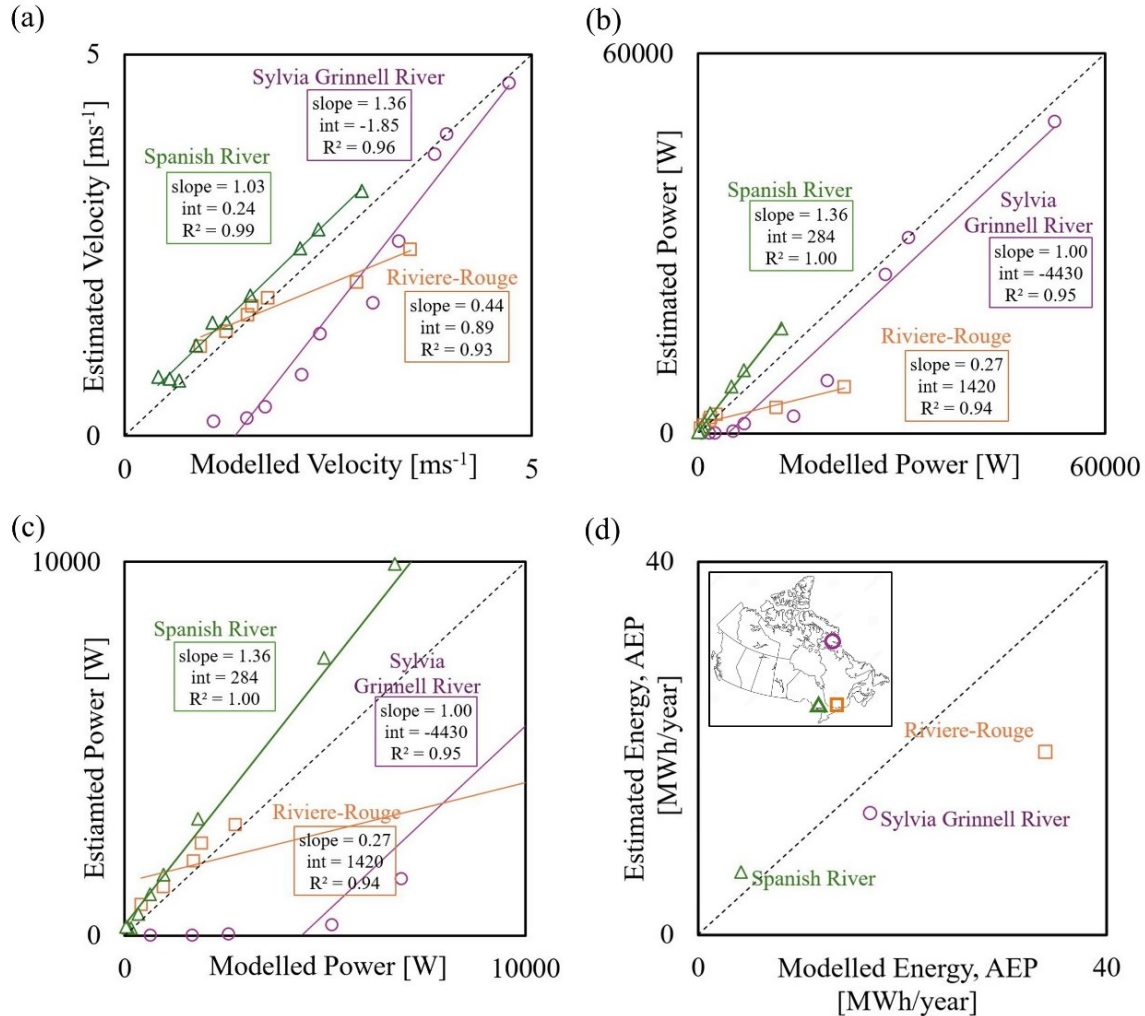


Figure 6-11: Validation results comparing hydrodynamic modelled values to estimates of (a) velocity; (b, c) power, with (c) zooming in on low-flow conditions to highlight trends; and (d) energy or AEP. The solid color lines represent the linear regression trends of the validation points, showing the relationship between estimated and modelled values. The hatched black lines indicate an ideal one-to-one relationship, where estimated values perfectly match modelled

6.3.4 Advancements and Limitations in the Large-Scale Estimation of River Hydrokinetic Energy

6.3.4.1 Advancements in River Hydrokinetic Energy Estimation

This study represents a significant improvement over earlier large-scale HKE assessments. The key advancements include higher spatial resolution, better incorporation of river width variability, and more accurate representation of channel morphology. Herein is a detailed comparison of the methodologies and findings.

Previous assessments, particularly Jenkinson and Bomhof (2014), overestimated the HKE potential of large rivers in low-to-moderate slope areas, such as the Mackenzie, Albany, Nelson, Peace, Saguenay, and Manicouagan Rivers. This overestimation was primarily due to underestimated river widths and bias in gauge station data, as identified by Jenkinson and Bomhof (2015; 2014) and also identified as a part of this work. The hydraulic geometry relationships used in these studies failed to capture the complex morphologies of wide, braided, or anabranching rivers. For example, rivers in low-gradient regions tend to widen significantly, which was not adequately accounted for in earlier models. Additionally, the hydraulic geometry relationships were derived from gauge station measurements, often collected at locations with lateral flow constrictions (e.g., bridges, dams, or weirs). This introduced a systematic bias, as these sites do not represent the full variability of river widths in natural settings (Krabbenhoft et al., 2022). By incorporating satellite-derived river widths, this study corrected these inaccuracies, providing more realistic HKE estimates for large rivers in low-gradient areas.

In contrast to low-slope rivers, mountainous regions with high topography and steep slopes were often correctly identified as high-potential areas in previous studies. However, the extent of their potential was understated due to resolution limitations and hydraulic geometry simplifications. Previous databases relied on coarse spatial resolutions, with cross-sections spaced kilometers apart, which failed to capture localized high-velocity zones in steep, narrow rivers. In addition, assumptions about channel morphology in steep regions led to underestimation of velocities and power potential. This study's use of moderate-resolution satellite imagery (cross-sectional spacing averaging 190 m) allowed for more precise identification of high-energy zones. For example, the Fraser River in British Columbia, located within the Fraser Canyon, was highlighted as a key area of HKE potential due to its extreme lateral constriction (Venditti et al., 2014). This finding underscores the importance of improved spatial resolution in accurately assessing HKE potential.

The improved resolution and accuracy of the CRHE database led to significant changes in the ranking of HKE potential across Canada's drainage basins compared to previous large-scale HKE assessments performed for Canada. The Pacific region now ranks highest for predicted HKE potential, followed by the Nunavik, St. Lawrence, and Maritimes regions, based on the mean AEP (Figure 6-7b) and excluding the Nelson basin, which has an inflated mean AEP due to flow estimate errors in the prairie regions. This contrasts with earlier studies, which ranked the Arctic and St. Lawrence regions above the Pacific. Both this study and previous assessments identified the Mississippi basin as having the lowest potential, based on mean AEP, due to its low-gradient terrain and smaller rivers.

Unlike previous studies, this database excludes rivers with a 0.01 percentile flow below 100 m³/s. This flow criterion, combined with the limitations of S2MSI imagery (20

m resolution), reduced the total stream length analyzed compared to Jenkinson and Bomhof (2014) from 1,731,000 km to 286,000 km. While this exclusion removed many small rivers, tributaries, and creeks, it ensured that only rivers with realistic HKE potential were included, aligning the database more closely with practical development scenarios.

Earlier databases featured significantly coarser reach-averaged spacing, with average reach lengths of 6.8 km (Ridgill et al. (2021)) and 5.6 km (Jenkinson and Bomhof (2014)). In contrast, this study achieved an average spacing of 190 m between cross-sections, providing greater accuracy and reduced overgeneralization. The finer resolution in this study enabled the identification of localized high-energy zones that were missed in previous assessments, and the improved spatial resolution reduced reliance on broad hydraulic geometry relationships, allowing for more nuanced predictions of HKE potential.

6.3.4.2 Study Limitations

This study considers only the theoretical maximum extractable resource and does not account for technical or practical assessment of the resource. Thus, engineering challenges for turbine design (e.g., turbine efficiency, deployment challenges, ice and debris, etc.) were not considered. Temporal variations in flow were considered in this study, but it was assumed that the HKE was extractable over the whole range of flows.

In reality, the true amount of extractable energy will be constrained by technical factors, including spatial variations in velocity through the river cross section; turbine design aspects such as efficiency, cross-sectional area, the degree of turbulent energy translation into extractable power, and the turbine's ability to divert debris; changes in velocity patterns due to turbine arrays or structures; and turbine downtime due to maintenance or other practical reasons. For example, HKE turbine power production and bedform shape were found to be significantly impacted by the effects of woody debris accumulation on the turbine (Aksen et al., 2025). Also, the amount of extractable power can be optimized using turbine designs that increase the capacity factor by changing rotors based on seasonal flow patterns (Shaabani et al., 2025). Additionally, practical limitations such as regional socio-economic conditions, proximity to electricity users or transmission infrastructure, and natural development barriers will further restrict extractable energy. However, design constraints – such as proximity to communities or the electrical grid – can be readily incorporated using GIS software. Similarly, filtering the dataset based on practical turbine installation criteria (e.g., minimum depth or velocity) is straightforward.

This study also does not take into account the impacts of climate change on rivers' hydrological cycles, channel stability, and channel migration. Although Canada's watersheds are not expected to experience severe or long droughts due to climate changes (Feng et al., 2025), the rainfall-runoff dynamics in Arctic watersheds may change with decreased permafrost and increased precipitation (McCrystall et al., 2021; Song et

al., 2021). Additionally, the dynamics of river ice in Canada are expected to change with a warming climate, reducing channel stability and increasing channel mobility (Lauzon et al., 2019). These impacts may make the estimates developed in this study unreliable if there are significant changes to hydrological regimes and river morphologies.

The greatest source of uncertainty is derived from the river depth and flow estimates. Specifically, the depth relationships are more applicable to non-regulated rivers, and some regions have a higher degree of confidence in the flow estimates based on data availability and strength of the derived relationships (Jenkinson and Bomhof, 2014). Despite these uncertainties, the resulting annual energy production (AEP) estimates remain valuable as a comparative metric. They allow for the identification of high-potential river sites for future field studies and refined resource assessments. If a region is identified as having high potential, the provided estimates can be easily refined using updated depth data from navigational charts, site observations, or high-resolution imagery. Flow estimates can also be refined through hydrological modelling or by referencing the Global Reach-scale A priori Discharge Estimates for SWOT (GRADES) dataset (Lin et al., 2019).

6.3.5 Guidelines for Further Assessment of River Hydrokinetic Energy Resources

If a river area or cross-section is identified as promising in the CRHE database, and further study of the area is desired to understand and characterize the resource, it is recommended that two steps be completed. The first step is a preliminary assessment using remote sensing. This includes the use of satellite imagery to identify favourable hydrokinetic conditions. For example, identifying sections of open water during winter months, when river ice is present elsewhere, may reveal localized areas of high velocity flow (d'Auteuil et al., 2019). Practical considerations of conducting HKE resource assessments, including communication with local stakeholders and field survey planning are recommended to be performed during this step (Kirby et al., 2023a). The second step is a comprehensive HKE assessment. This step includes conducting field data collection and hydrodynamic modelling following established guidelines, such as the International Electrotechnical Commission's Specifications for River Hydrokinetic Energy Assessments (IEC, 2019). Resources such as Postacchini et al. (2025), Kirby et al. (2023b), and Duvoy and Toniolo (2012) provide detailed methodologies for such studies.

6.4 Conclusions and Recommendations

The Canadian River Hydrokinetic Energy (CRHE) database, a high-resolution national database of river HKE for Canada, was developed by utilizing satellite-derived river width measurements and complementary data to improve the accuracy of HKE resource estimation. With an average spacing of 190 m between measurements and 100

m spacing for rivers under 200 m in width, it is the first time that a HKE database effectively captured changes in river morphology on a cross-sectional basis and identified areas of high energy potential due to changes in channel geometry on such a fine scale. In particular, this study found high energy cross sections in regions with significant topographical variations such as British Columbia, Eastern Ontario, Quebec, and Eastern Manitoba. Validation efforts confirmed good agreement between derived, field-measured, and modelled parameters, although depth estimation emerged as a primary source of error in velocity and energy calculations. Because this study estimates the theoretical maximum extractable resource, and does not take into consideration proximity to communities or electrical grids, ice and other practical engineering challenges, and ecological impacts of the turbines, further study is required when a river location is identified as potentially feasible. This includes detailed resource estimation, numerical modelling of hydraulic changes and their ecological impacts, ice impact studies, and study on the socioeconomic readiness of the local area for energy transition.

From the national analysis, the Pacific drainage basin emerged as the most promising region for HKE extraction, followed by the Maritimes, as well as the Nelson and St. Lawrence River basins. Mountainous regions with constricted rivers, such as the Fraser River, have high HKE potential. Furthermore, the database's improved spatial resolution and exclusion of smaller rivers enhanced the ability to identify locations of potential HKE development compared to earlier assessments, increasing the usefulness of the dataset. Large rivers in low to moderately sloped areas have low HKE potential, and this was not properly ascertained in previous national or global HKE databases. Velocity and power estimates were validated against field data and hydrodynamic models, revealing good general accuracy. However, errors were most often linked to depth underestimation, especially in regulated rivers or those with unique flow structures (e.g., dam-affected rivers like the Rideau River or rivers in canyons such as the Fraser River). As such, validation highlighted the need for better depth estimates, potentially through remote sensing techniques, and improved flow estimates, potentially via localized hydrological modelling or remote sensing algorithms, to further refine velocity and energy calculations. Satellite imagery was limited by resolution (20 m for S2MSI imagery) and coverage constraints, affecting smaller rivers and regions with cloudier and snow/ice conditions. Regions with narrower rivers (e.g., Maritimes, Yukon, Mississippi, and Pacific drainage basins) or persistent snow and cloud cover (e.g., Western Canada and Arctic) had fewer usable satellite measurements.

The CRHE database represents a significant advancement in understanding and harnessing Canada's HKE resources. It offers a detailed, validated, and spatially precise tool to guide policymakers, energy developers, and local communities in identifying viable locations for HKE development. By addressing limitations related to depth and flow

estimation, the database's accuracy and applicability can be further enhanced, paving the way for sustainable energy generation in Canada.

Chapter 7. The Renewable In-Stream Energy Potential of Arctic Rivers for Remote Communities

This chapter is a preprint of a modified version of the following published article:

Kirby, K., Rennie, C.D., Nistor, I., Johnstone, C., Ordonez Sanchez, S., Fu, S., Cousineau, J., Ferguson, S., Shilton, H., 2026. The in-stream renewable energy potential of rivers for remote communities in the global Arctic. Manuscript submitted for publication (under review in Nature Communications).

Abstract:

Many Arctic communities remain reliant on diesel-generated electricity, resulting in high costs, environmental impacts, and constrained development. Hydrokinetic energy (HKE) offers a lower-impact alternative to conventional hydropower, which often faces ecological opposition. This study evaluates HKE technical and socioeconomic feasibility through (i) a detailed case study of the Iqaluit Kuunga River in Nunavut, Canada, (ii) a global analysis to identify feasible communities, and (iii) an examination of Arctic socioeconomic readiness for energy transition. The Iqaluit Kuunga River case confirmed turbine deployment viability, and 325 global Arctic communities were identified as feasible for HKE in open water conditions, representing a theoretical total of 4,626 MWh/year per square metre of turbine area. Community-level feasibility varied based on the local resource availability, proximity to river sites, and projected diesel offset. The resulting datasets support future exploration of renewable energy transitions in remote Arctic regions by providing a foundation for targeted HKE development.

7.1 Introduction

The growing push to develop renewable energy (RE) is fuelled by extensive evidence of the negative environmental impacts of fossil fuel-based energy sources (Kuzemko et al., 2016). As of 2021, 79% of Arctic communities in Canada, Greenland, and Alaska, US, still relied on diesel for electricity (de Witt et al., 2021). This reliance has caused environmental degradation and hindered community development. In Canadian Indigenous communities, diesel-based electricity generation has compromised service quality and impeded innovation (Agu et al., 2023).

All Arctic regions, reliant on seasonal navigation and winter roads, face logistical challenges in delivering diesel (Gritsenko and Salonen, 2021). Additionally, black carbon from fossil fuels accelerates local ice and snow melt, reducing the Arctic's reflectivity (Gritsenko and Salonen, 2021; Kholod et al., 2016) and altering historical ice stability patterns. These changes lead to increased risk for hunters traveling to traditional hunting

areas. Further, market fluctuations tied to fuel shipping and storage have only added to the complexity of development (Gritsenko and Salonen, 2021). Thus, communities are seeking alternatives due to the high costs, environmental risks, and long-term sustainability concerns of diesel (Weis et al., 2008).

The Arctic is home to a growing population of approximately four million people (Fondahl et al., 2015). Yet, its vast geography presents energy challenges due to mountains, tundra, and extreme cold weather conditions (de Witt et al., 2021). Key challenges for energy availability in the Arctic include costly transportation, limited infrastructure, and environmental and health risks (Mortensen et al., 2017). In Canada, 65% of energy is produced from renewable sources, but this rarely benefits remote Arctic communities disconnected from the southern grid (Karanasios and Parker, 2018). Energy costs in Arctic Canada are also among the nation's highest (Pinard et al., 2023). In Nunavut, 20% of the government's annual budget subsidises diesel-based electricity (McDonald and Pearce, 2013), diverting funds from pressing needs such as mental health, housing, and food security. Similarly, in Arctic Russia, monopolies and high electricity prices strain households financially, where prices reach 600 rubles (~7.5 USD) per kWh compared to the national average of 3 rubles per kWh (Gritsenko and Salonen, 2021). Existing energy systems in these regions operate at a deficit, forcing utilities to pass costs onto consumers (Weis et al., 2008). With energy availability being critical for survival, especially in low-income communities in extreme environments, addressing these barriers is essential for improving Arctic energy sustainability (de Witt et al., 2021).

Community studies in Nunavut, Canada, show strong support for RE adoption, with little backing for continued diesel use (Nunavut Nukkiksautiit Corporation, 2023a, 2023b, 2023c). Hydropower already plays a large role, accounting for 44% of global Arctic electricity compared to 16% globally (de Witt et al., 2021). However, hydropower development in Arctic Canada has faced opposition due to environmental and social concerns, including the flooding of Indigenous lands and treaty violations (Karanasios and Parker, 2018; McDonald and Pearce, 2013; Nunavut Nukkiksautiit Corporation, 2024).

Hydrokinetic energy (HKE) presents a promising alternative to traditional hydropower by harnessing run-of-river currents without requiring dams. Unlike conventional hydropower, hydrokinetic turbines minimize impact to river ecology (Hill et al., 2014) and sediment transport (Batalla et al., 2021; Cada et al., 2007; Kondolf et al., 2014). The Arctic's HKE is notable, with rivers (excluding Greenland) expected to produce 2,000 TWh annually (Ridgill et al., 2022, 2021). HKE viability was demonstrated in Igiugig, Alaska, where a single turbine cut diesel use by 50% during peak demand and reduced emissions by 98.7% (McCallum et al., 2021). Additionally, small hydrokinetic systems are relatively simple to install and maintain, making them a practical solution for remote Arctic communities (Vermaak et al., 2014). However, feasibility in Arctic rivers with long ice

cover requires examination. To continue to drive this technology forward, further studies on HKE are necessary, focusing on optimal sizing, reliability, and policy support (Vermaak et al., 2014).

To support the development of policies for the exploration and development of HKE in the Arctic, a feasibility assessment of HKE in the Arctic is presented, specifically examining the Iqaluit Kuunga River in Nunavut, Canada. Additionally, HKE resources are analysed broadly across the Global Arctic to identify strategic locations for deployment, considering technical, community, and socio-economic factors. By advancing HKE research, this study aims to support sustainable and locally beneficial energy solutions for Arctic communities.

7.2 Methods

7.2.1 General Approach

This study employed a four-tiered methodology to evaluate the feasibility of hydrokinetic energy (HKE) extraction in remote Arctic communities. The first tier involved a site-specific assessment of the HKE resource on a representative Arctic river – the Iqaluit Kuunga River (English name: Sylvia Grinnell River) near Iqaluit, Nunavut, Canada. This included in-situ data collection and subsequent hydrodynamic modelling to estimate the theoretical HKE potential. The second tier focused on identifying remote and rural communities within Canada with favourable conditions for HKE deployment. This national-scale assessment was conducted independently of the global analysis as the data available for river HKE and remote communities in Canada are more detailed than its global counterparts. The third tier involved a global assessment of riverine HKE resources across the Arctic and sub-Arctic, with the objective of identifying additional rural and remote communities potentially suitable for HKE implementation. The fourth tier of the assessment focused on the evaluation of socioeconomic readiness and community-level capacity for HKE adoption, considering institutional, financial, and logistical factors critical to renewable energy transition in isolated Arctic regions. This final tier aimed to contextualize the technical findings, addressing the practical enablers and barriers to HKE deployment beyond resource availability alone.

7.2.2 Field Data Collection at Candidate River Site

The case study of HKE resources in a northern river was conducted on the Iqaluit Kuunga River near Iqaluit, Nunavut, Canada in accordance with the International Electrotechnical Commission's (IEC) standards for river HKE resource estimation and current methods (IEC, 2019; Kirby et al., 2023b). The daily average temperature is -8.6 °C, and the mean annual precipitation is 361.2 mm, comprising 216.6 mm rainfall and 190.0 cm snowfall (Environment and Climate Change Canada, 2025). The river's hydrology is primarily driven by snow and ice melt, resulting in a short, high-flow period

that typically occurs from late June to early July. Two surveys were performed on July 9, 2023 and August 10, 2023 to characterize a high flow ($203 \text{ m}^3/\text{s}$) and low flow ($33 \text{ m}^3/\text{s}$) event, respectively, using a four-beam acoustic Doppler current profiler (ADCP; SonTek M9). The ADCP was deployed using a remote-controlled boat (Oceanscience Q-Boat). During each survey, six transects at a uniform cross section were taken for discharge measurements, three-dimensional velocity profiles were collected in a zigzag pattern with approximate 1/5 river width spacing, and stationary velocity data were collected at the location of highest velocity where the boat could be sufficiently piloted in a stationary position, designated as the optimal turbine location (OTL; Figure 7-1). The sampling frequency was 1 Hz.

The upstream boundary of the survey was determined by the maximum speed that the boat was able to maintain in the rapids without being overtopped. Bathymetry data (riverbed elevation) and water surface elevation data were also collected from the ADCP surveys. The collected ADCP data was geospatially corrected with real-time kinematic differential global positioning system (RTK-DGPS). Due to the high-latitude field conditions and limited satellite availability, the GPS receiver's azimuth mask angle was reduced from 15° to 10° to increase the number of visible satellites on the horizon in order to employ RTK-DGPS. Research permissions for data collection were granted by the Nunavut Research Institute and the Amarak Hunters and Trappers Association in Iqaluit, Nunavut.

7.2.3 Numerical Hydrodynamic Modelling Hydrokinetic Energy

Hydrodynamic modelling was performed using TELEMAC-2D and TELEMAC-3D, open-source finite element-based numerical hydrodynamic modelling software that solves the shallow water equations and the Navier-Stokes equations, respectively, for simulating free-surface flow (Hervouet, 2007). The computational domain was discretized using an unstructured triangular mesh with a uniform node spacing of 2 m, generated in Blue Kenue® (Canadian Hydraulics Centre, 2011). The shoreline topography was derived from the CanElevation Series High Resolution Digital Elevation Model (HRDEM) (Natural Resources Canada, 2022), which provides surface elevations in 1 m resolution.

Model calibration was performed by adjusting the bed roughness (represented with the Strickler coefficient), the velocity diffusivity (via the eddy viscosity), and the upstream bathymetry elevation to minimize the root mean squared error (RMSE) and mean absolute percent error (MAPE) between simulated velocity fields and in-situ ADCP measurements for both measured flow conditions. The bed roughness and eddy viscosity were iteratively adjusted following sensitivity analysis, resulting in optimal calibrated values of $30 \text{ m}^{1/3}/\text{s}$ and $0.05 \text{ m}^2/\text{s}$, respectively. To facilitate accurate simulated flow direction and magnitude into the OTL, the upstream bathymetry was calibrated using the points illustrated in Figure 7-1. This refinement ensured convergence between modelled and observed flow characteristics within the turbine deployment zone.

To calculate the HKE resource in a typical year of turbine operation, the International Electrotechnical Commission's (IEC) guidelines for river hydrokinetic energy resource assessment (IEC, 2019) were followed. For flow characterization, FDCs were generated from the Water Survey of Canada daily hydrometric data from gauge 10UH001 for years 1971-2021 (Figure 7-2b). The impact of ice conditions on the theoretical HKE amount was incorporated by defining two distinct operational scenarios: a "short-season" year characterized by delayed ice break-up and early freeze-up, and a "long-season" year with early ice break-up and late freeze-up. Two separate FDCs were generated for each condition as maximum and minimum resource estimates. The 51 years of hydrometric gauge measurements were therefore separated into long- and short-season categories. Twelve years of data (1987-1988, 1991, 1997-1998, 2000, 2001-2005, 2016) were removed from the analysis due to missing or incomplete data. The remaining 40 years were categorized into 25 short-season years (1971-1972, 1974, 1976-1984, 1986, 1989-1990, 1992, 1996, 1999, 2007, 2013, 2015, 2017-2018, 2020-2021) with more ice-covered days and 14 long-season years (1973, 1975, 1985, 1993-1995, 2006, 2008-2012, 2014, 2019) with fewer ice-covered days, and separate FDCs were generated for each subset to represent minimum and maximum theoretical HKE availability, respectively. To validate the seasonal classification and the accuracy of Water Survey of Canada ice condition labels (i.e., "ice-covered" measurement labels), visual confirmations of ice break-up and formation timing were performed with Sentinel-2 Level 2A multispectral satellite imagery for years 2016-2024.

Ten representative flow conditions from each FDC were chosen to represent the entire distribution of flow exceedance probabilities (Figure 7-2b). For each selected discharge, velocity flow fields were generated using the previously calibrated and validated TELEMAC hydrodynamic model (Figure 7-2c.1-3). These simulations yielded corresponding velocity duration curves (VDCs; Figure 7-2d) at the OTL. The mean stream-wise, depth-averaged velocity at the OTL was used to calculate the power using Equation 1, resulting in the generation of power duration curves (PDCs, Figure 7-2e). The PDCs were interpolated using Equation 2 to calculate the AEP.

$$[7-1] P = \frac{1}{2} A \rho v^3$$

$$[7-2] AEP = N_h \sum_{i=1}^{N_b} P_i B_i$$

where P is the hydrokinetic power (W), A is the turbine cross-sectional area (assumed to be 1 m² for standardization), ρ is the density of water (kg/m³), v is the flow velocity (m/s), AEP is the annual energy production (MWh/year/m²), N_h is the number of turbine operation hours in a year (hours), i is the number of points on the PDC, P_i is the power at a particular flow exceedance (W), and B_i is the width on the PDC that the point represents as a decimal probability.

Because the Iqaluit Kuunga River freezes to the riverbed in the winter at the investigated location, the hydrokinetic turbine would need to be removed prior to freeze-up in the fall and reinstalled post ice break-up in the spring (mean season length of 103 days). This seasonal deployment schedule was explicitly integrated into the AEP estimation through the method used to construct the seasonal FDCs, ensuring that resource availability reflects realistic operational windows.

7.2.4 Technical In-Stream Hydrokinetic Potential for Remote Canadian Communities

To identify remote Arctic and sub-Arctic communities in Canada with potential for HKE deployment, two national geospatial datasets were utilized: the Canadian River Hydrokinetic Energy (CRHE) database (Kirby et al., 2026) and the Remote Community Energy Database (RCED) (Government of Canada, 2016). The CRHE database includes estimates of HKE for all rivers in Canada that can exceed 100 m³/s at any point in their hydrological cycle and are greater than 20 m in width. The river HKE estimates in the CRHE were derived using a multi-step methodology: discharge estimates were extracted from two datasets of (i) modelled flows in southern Canada obtained by multiple linear regression and canonical correlation analysis informed by Water Survey of Canada flow records (Jenkinson and Bomhof, 2014) and (ii) modelled flows in northern Canada obtained by downscaling hydrological data and converting runoff estimates into streamflow via the WATROUTE routing scheme (Teufel and Sushama, 2022); river depth was estimated from hydraulic geometry relationships (Jenkinson and Bomhof, 2014); and river width was extracted from Sentinel-2 multispectral satellite imagery (Kirby et al., 2026).

A proximity analysis was performed between river cross sections exceeding a theoretical HKE density of 10 MWh/year/m² and the 178 communities in the RCED. Communities within a 10 km radius of these cross sections were flagged as candidates for HKE integration. Using community-level data from the RCED, including annual energy consumption (in MWh/year) and primary electricity generation source, the potential diesel offset achievable by a single hydrokinetic turbine was estimated for each community. Furthermore, a statistical correlation analysis using the coefficient of determination (R^2) was conducted to evaluate the relationship between mean annual air temperature and community energy consumption, with the objective of determining whether colder communities, which typically exhibit higher heating-related electricity demand, correlate with lower diesel offset potential. This analysis aimed to assess how climatic factors might influence the technical and economic feasibility of HKE adoption in northern remote communities.

7.2.5 Calculation of Technical In-Stream Hydrokinetic Potential for Global Arctic Communities

To identify communities feasible for river hydrokinetic energy deployment in the Global Arctic, estimates of HKE were derived using Equations 1 and 2 for all rivers above 55°N. Community locations were extracted from the Geographic Names Server (GNS), a geospatial database maintained by the National Geospatial-Intelligence Agency that contains standardized place names approved by the United States Board on Geographic Names (National Geospatial-Intelligence Agency, n.d.). A proximity analysis was performed between community locations and river cross sections with an estimated HKE exceeding 10 MWh/year/m². Communities located within 10 km of a favourable river location were identified as candidates for HKE deployment.

The HKE estimates were derived using a methodology consistent with that applied to the Iqaluit Kuunga River case study, wherein flow, velocity, and power duration curves were developed to compute AEP for each river cross section. To generate the FDCs, the Global Reach-level A priori Discharge Estimates (GRADES) dataset (Lin et al., 2019) was used which contains model-derived daily discharge estimates for 1980-2013 at a global scale. The GRADES dataset was calibrated using streamflow characteristics rather than parameter regionalization, resulting in improved model performance even at ungauged locations (Yang et al., 2019). The FDCs from the GRADES data were spatially coupled to river locations using MERIT hydro streamlines (Yamazaki et al., 2019).

River channel geometry was estimated from two sources: river depth from hydraulic geometry relationships (Jenkinson and Bomhof, 2014; Kirby et al., 2026), relationships between river depth and river flow that were derived at Water Survey of Canada hydrometric gauge stations (Bomhof, 2014; Jenkinson and Bomhof, 2014), and river width from the Global River Widths from Landsat (GRWL) dataset (Allen and Pavelsky, 2018). The GRWL dataset includes estimates of river width at mean annual flow with an average spatial resolution of 35 m. A rectangular channel shape was assumed. VDCs were derived for each cross section by estimating the cross-sectional mean velocity for each FDC exceedance probability by conservation of mass, using the derived river depth at each flow exceedance and a constant river width at mean annual flow. Because multiple width measurements across different flow conditions are not available globally in the GRWL dataset, as they are in the CRHE database, estimates of velocity at high exceedance and low exceedance probabilities on the VDC are likely to contain some error. The power at each exceedance was calculated using Equation 1, assuming a turbine cross-sectional area of 1 m² for standardization across sites. The resulting PDCs were interpolated using Equation 2 to compute the AEP at each river cross section.

7.2.6 Socioeconomic Status of Renewable Energy Transition in the Global Arctic

Feedback on river HKE development and broader renewable energy transition efforts in Arctic regions was collected through in-situ community engagement during fieldwork near Iqaluit, Nunavut, Canada, and via structured knowledge dissemination events involving local residents. In particular, the authors gathered data regarding barriers to renewable energy transitions in their communities, the general interest in renewable energy systems, and if the participants expected any benefits from renewable energy in their communities. The participants were also asked if there were any foreseeable challenges to hydrokinetic energy deployment in their communities. Participants were asked open- and closed-ended questions to elicit insights on institutional, financial, technical, and logistical constraints to renewable energy deployment. To complement the empirical feedback, a comprehensive literature review of renewable energy transitions across the global Arctic was conducted. Both sources of information, primary community input and secondary literature, were categorized into four identified thematic categories: funding and costs, capacity, current energy structures, and community-based energy. Key findings from both the community engagement and literature review were mapped to these categories to identify recurring challenges and enabling conditions. For example, training requirements for new energy systems were interpreted as both a capacity issue and a cost-related barrier, given the requirement for both time investment and financial resources. Categorizing the key findings provided a structured framework for interpreting the multifaceted social and institutional dynamics that shape renewable energy deployment in remote Arctic communities.

7.3 Results and Discussion

7.3.1 Hydrokinetic Energy Feasibility Assessment of an Arctic River

To address the knowledge gap on HKE viability in the Arctic, a case study was conducted on the Iqaluit Kuunga River (Sylvia Grinnell River), located 5 km northwest of Iqaluit, Nunavut, Canada (63.787 °N, -68.622 °W). With an annual average air temperature of -8.6 °C (Environment and Climate Change Canada, 2025), the site is colder than 97.5% of the 3,129 northern communities identified in this study above 55 °N. The HKE resource was assessed using field data (Figure 7-1) and hydrodynamic modelling (Figure 7-2), confirming the site's technical feasibility for turbine deployment. Theoretical energy potential was estimated at 16.8 MWh/year per m² of turbine capture area, with velocity consistently above 1.0 m/s, even in late summer low flow conditions, a value often cited as an indicator of HKE feasibility (Kumar and Saini, 2016).

Given Nunavut's per capita electricity use of 6.03 MWh/year (Canada Energy Regulator Government of Canada, 2024), a 10 m² Savonius turbine with an optimized coefficient of power of 0.45 (Kumar and Saini, 2016; Niebuhr et al., 2019) could potentially

supply electricity to 12-13 people. Because turbines are generally deployed in arrays (Chen et al., 2024), this estimate is conservative. Using the ORPC RivGen (McCallum et al., 2021; ORPC, 2023) turbine power curve, the site's AEP is projected at 95-105 MWh/year during open water months for a single turbine, considering a 1 m/s cut-in and 3.5 m/s cut-out velocity. Adjusting for operational days, this energy yield is comparable to the Kvichak River installation in Igiugig, Alaska, which produces 349 MWh/year and offsets 60–90% of community diesel use. (McCallum et al., 2021; ORPC, 2023).

To derive these estimates of HKE resource at the study site, field data were collected with an acoustic Doppler current profiler (ADCP) mounted on a remote-controlled boat (Figure 7-1). This provided three-dimensional velocity, bathymetry, and water surface elevation. These data identified the optimal turbine location (OTL; Figure 7-1b) to be directly downstream of a river width constriction. Here, flow velocity is increased by lateral narrowing and an elevation drop, creating a scour hole of 6 m (high flow) to 3m (low flow). The combination of increased streamwise velocity and greater depth makes this site ideal for turbine deployment. Similar features may indicate suitability for HKE development elsewhere.

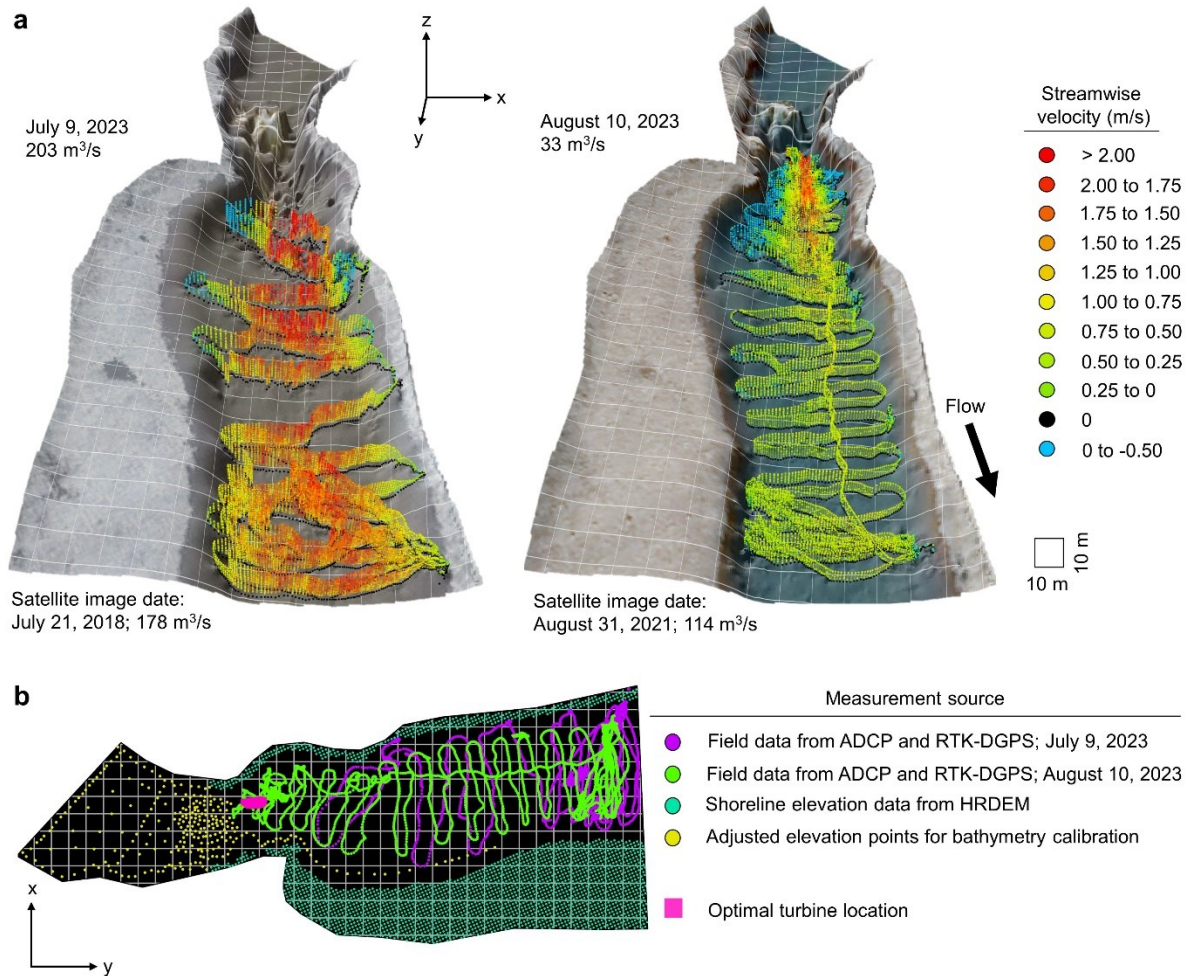


Figure 7-1: Field data collected at the Iqaluit Kuunga River, Nunavut, Canada to support HKE resource estimation and turbine staging. (a) Acoustic Doppler current profiler measurements under two distinct flow conditions. (b) Spatial coverage and sources of riverbed bathymetry, water surface elevation, and three-dimensional flow velocity data. Upstream riverbed elevation points were adjusted near the width constriction and elevation drop to calibrate the hydrodynamic model, aligning simulated velocities with field measurements. The optimal turbine location (OTL) is shown in pink, as determined by water depth and flow velocity thresholds.

At the Iqaluit Kuunga site, the river freezes completely to the bed, as shown in the hydrograph (Figure 7-2a); thus, HKE was calculated only the open water season. Ice conditions would necessitate seasonal turbine removal and reinstallation to mitigate damage, resulting in less energy production and higher labour costs for this site. In contrast, the community of Igiugig, Alaska, with a higher mean annual temperature of 1.9 °C, has reported no turbine ice issues during operation over two winters (Hill and Paris, 2023). Logistical and engineering challenges of this nature were not further explored in this study, as these challenges will vary at each river location.

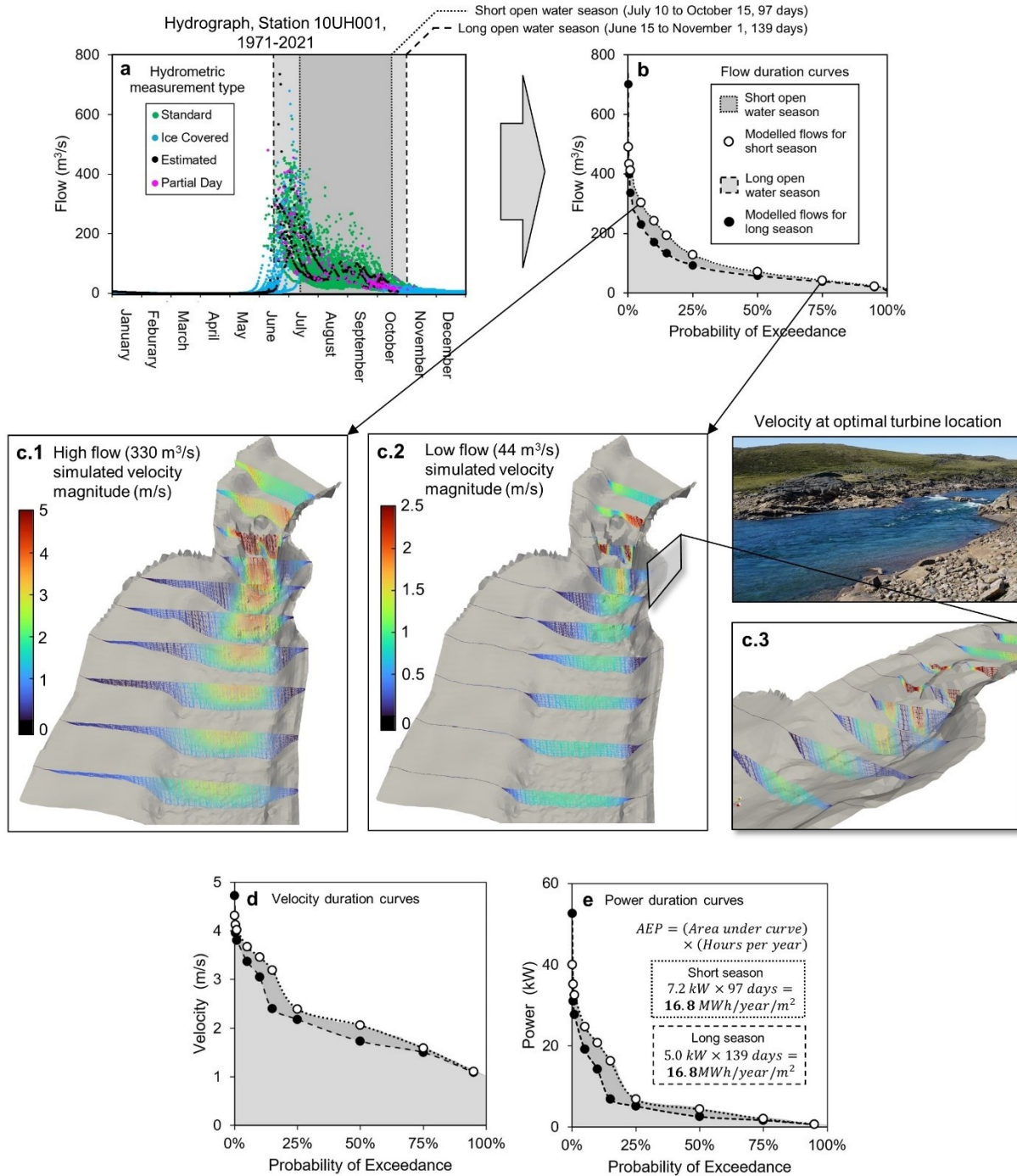


Figure 7-2: **Hydrodynamic modelling and HKE analysis for the Iqaluit Kuunga River site.** (a) Site hydrograph from 51 years of hydrometric data located 5 km downstream from the site, also indicating the two scenarios used to calculate the HKE: a typical short open water season and a typical long open water season based on observations of break up and freeze up times from satellite imagery and the hydrometric

data. (b) The two flow duration curves generated from only the standard hydrometric measurement data (ice covered, estimated, and partial day measurements removed) representing a short open water season and a long open water season. (c.1) Simulated velocity flow field for a high flow condition ($330 \text{ m}^3/\text{s}$) from the calibrated (root mean squared error, RMSE, of 0.34 m/s and mean absolute percent error, MAPE, of 22.0%) and validated (RMSE of 0.26 m/s and MAPE of 10.5%) hydrodynamic model. (c.2) Simulated velocity flow field for the low flow condition ($44 \text{ m}^3/\text{s}$). (c.3) Simulated velocity flow field at the optimal turbine location for the low flow condition ($44 \text{ m}^3/\text{s}$), similar to the low flow condition measured on August 10, 2023 ($33 \text{ m}^3/\text{s}$; Figure 1b) shown for visual comparison. (d) The two velocity duration curves for the site, based on the simulated velocity data. (e) The two power duration curves for the site and associated annual energy production (AEP) for each of the two open water conditions.

The hydrodynamic model, calibrated and validated with ADCP data (Figure 7-1), simulated a range of representative flows at the site. Two flow duration curves (FDCs; Figure 7-2b), derived from the site hydrograph, informed the selection of twenty flow conditions, ten each for long and short open water seasons. Velocity fields (Figure 7-2c.1-2c.2) were simulated for these conditions to estimate OTL velocities (Figure 7-1b, Figure 7-2c.3) and generate corresponding velocity duration curves (Figure 7-2d). Simulations showed that velocities at the OTL consistently exceeded 1.0 m/s during open water periods. The annual energy production (AEP), calculated from the power duration curves (Figure 7-2e), was similar for both season lengths due to higher early-season flows in the short season, likely driven by concentrated melt events. However, ice presence during these high flows may hinder turbine deployment, reducing actual energy capture relative to theoretical estimates.

7.3.2 Technical In-Stream Potential near Remote Communities in Canada

Building on the Iqaluit Kuunga River case study, the analysis was extended to evaluate HKE potential across the Canadian Arctic and sub-Arctic. Each remote community was assessed using the Canadian River Hydrokinetic Energy (CRHE) (Kirby et al., 2026) and Remote Communities Energy (RCE) (Government of Canada, 2016) databases, which provide detailed, nationally sourced data on hydrokinetic potential and electricity generation profiles, including electricity source and amount, for the 178 remote communities in the RCE database.

Figure 7-3a-c show community locations, proximity to rivers, and population distribution, respectively. Most communities (64%) are within 10 km of a river, and 79% of communities rely primarily on diesel for electricity. Few communities have populations exceeding 1,000 people, and the median inter-community distance is 77 km (IQR 47-122 km). An estimated 17,500 km of transmission lines would be needed to interconnect all communities, indicating the practicality of community-based electricity generation on local microgrids as opposed to centralized grid integration (Uddin et al., 2023).

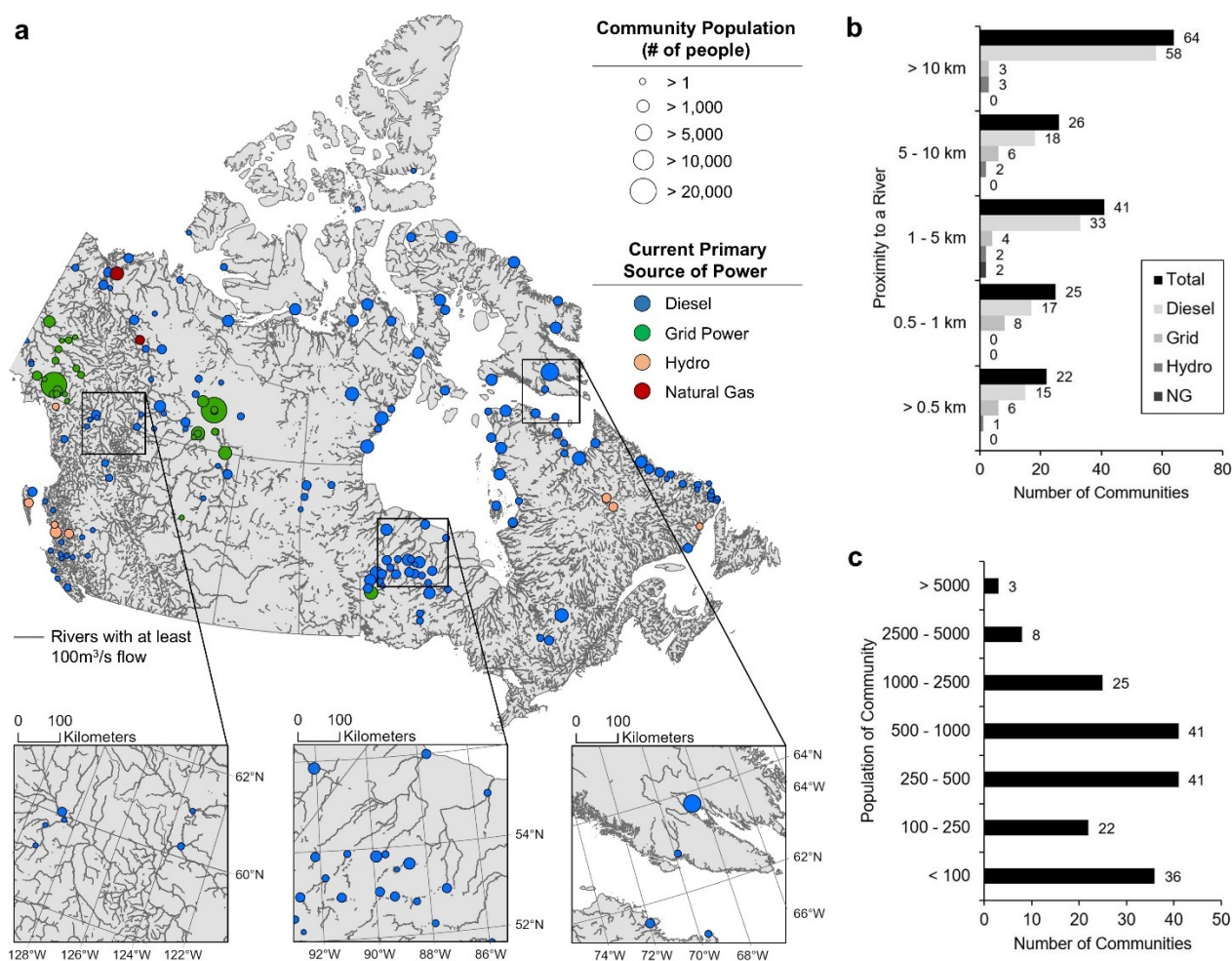


Figure 7-3: Remote Arctic and sub-Arctic communities in Canada with river proximity and population distributions. (a) Remote communities in Canada, most of which are First Nations or Inuit (28.7% Inuit, 61.8% First Nations, 4.5% Indigenous Collective, 5.1% non-Indigenous), and their primary source of electricity generation as well as the community population. (b) Community proximity to rivers and current primary power generation. Communities within 10 km of a river and currently on diesel-based electricity generation are most likely to be feasible for and benefit from HKE. (c) The division of communities into population categories.

Figure 7-4a highlights communities within 10 km of river sites with HKE exceeding 10 MWh/year/m². Because the CRHE dataset represents rivers with flows greater than 100 m³/s, there is still a small likelihood that communities not included in Figure 7-4a may still be feasible for HKE.

A total theoretical maximum AEP of 1,770 MWh/year/m² is estimated from the 50 remote communities identified to be feasible. Using fossil fuel generation data from the

RCE database (Government of Canada, 2016), ten communities could achieve greater than 20% diesel offset with a single turbine, and fifteen could achieve greater than 5%. Among the 50 identified communities, the median diesel offset from one turbine was 6.7% (IQR 3.1-27.8%).

No correlation was found between the mean annual air temperature over the 1994-2024 period (Figure 7-6a) and the per-capita fossil fuel-based electricity usage for the 178 communities in the RCE database ($R^2=0.076$), excluding communities with major industrial activity (i.e., mining, forestry, etc.). Thus, despite a 23°C range in mean community temperatures (median -3.5°C; IQR -7.2 to -0.35°C), energy use was not temperature-dependent. Similarly, no correlation was found between temperature and diesel offset from HKE ($R^2 = 0.040$), indicating that, given suitable river conditions (i.e., power, ice, and installation conditions), colder communities can benefit from HKE just as much as warmer ones.

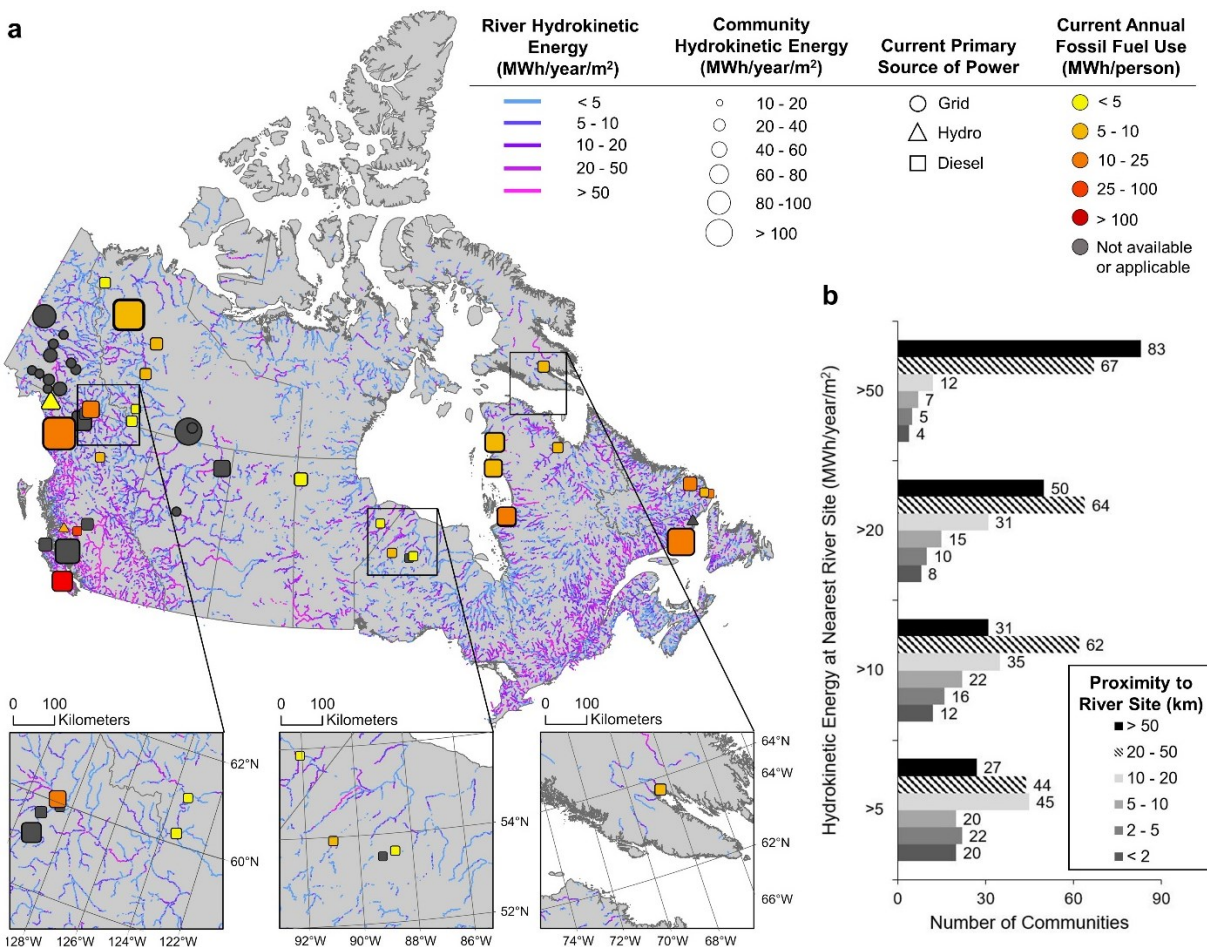


Figure 7-4: Remote Canadian communities identified as feasible for HKE development. (a) The Canadian River Hydrokinetic Energy (CRHE) database and remote communities in Canada within 10 km of a 10 MWh/year/m² hydrokinetic river

site. Communities are symbolized by the estimated amount of river HKE available near the community (size), the current main electricity source (shape), and community's current annual per capita fossil fuel use (colour). The communities currently reliant on diesel with a high nearby river HKE resource are the most promising for turbine deployment. (b) A bar graph detailing the distribution of communities between their distance to the nearest feasible hydrokinetic river site and the amount of potential energy at the nearest river site.

7.3.3 Global Arctic Technical In-Stream Potential near Communities

The HKE feasibility analysis was expanded to the global Arctic, where available data is less detailed than in Canada. River energy estimates were derived from global databases (see Methods) to identify communities suitable for hydrokinetic development. Figure 7-5 illustrates Arctic and sub-Arctic communities with populations under 10,000 to focus this analysis on remote, small communities. Of the 3,129 communities identified, 1,007 are within 10 km of a river. Figure 7-5 includes national electricity source distributions from the International Energy Agency (International Energy Agency, 2022). The contrast between Arctic and national energy profiles, illustrated for Canada, demonstrates that national statistics often fail to capture conditions in remote regions. Nonetheless, these distributions provide useful context by highlighting countries with high fossil fuel use that may be well-suited for HKE transitions.

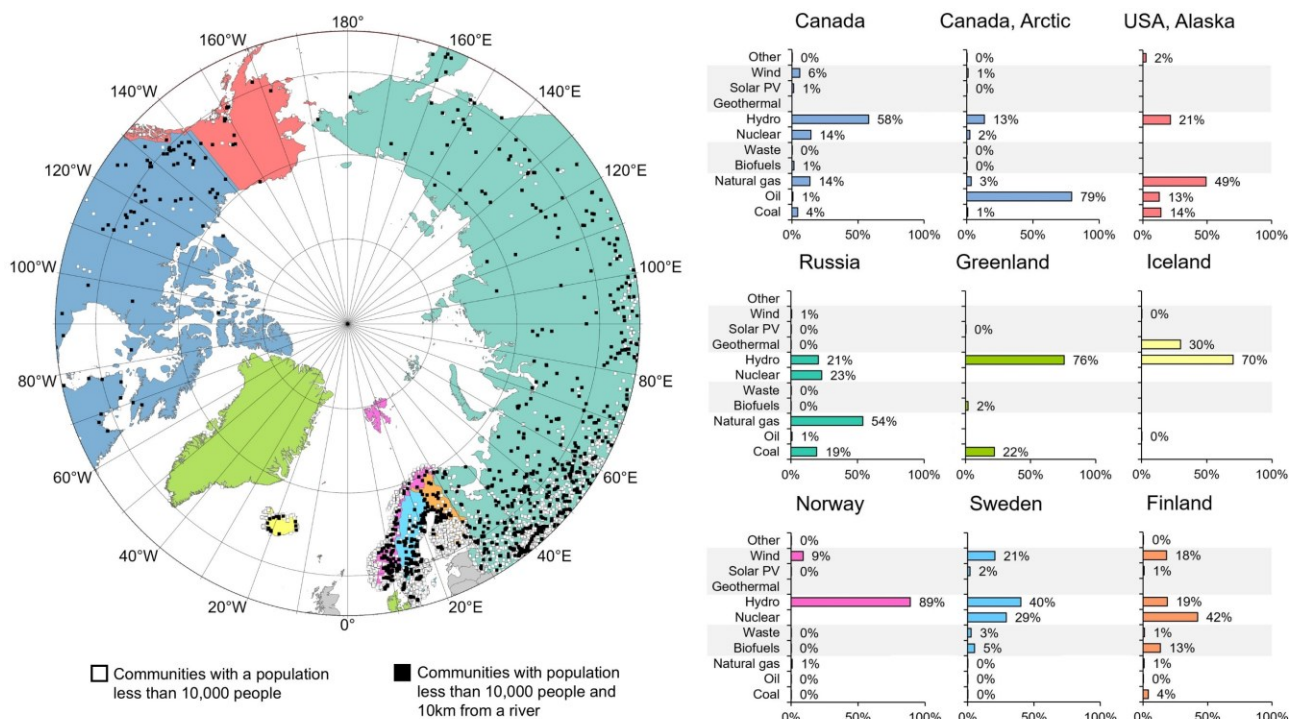


Figure 7-5: **Communities with a population of less than 10,000 people north of 55°N latitude.** Communities located within 10 km of a river are indicated in black. Each country considered in this analysis is listed to the right with the percent of total electricity

in the countries also illustrated. The comparison between the Canadian Arctic and wider Canada illustrates the disparity between northern communities' electricity sources and the rest of the country.

The total AEP for Global Arctic communities was estimated at 4626 MWh/year/m² across 325 identified communities (Figure 7-6a). For Canada, the global approach yielded 684 MWh/year/m², compared to 1,326 MWh/year/m² from the national assessment. Similarly, 31 feasible Canadian communities were identified globally versus 50 nationally. This discrepancy reflects differences in data resolution, with the CHRE database incorporating more detailed river channel dimensions and a more comprehensive river network. Consequently, the global assessment likely underestimates AEP, though both datasets showed good agreement with validation data at three sites (Figure 7-6b).

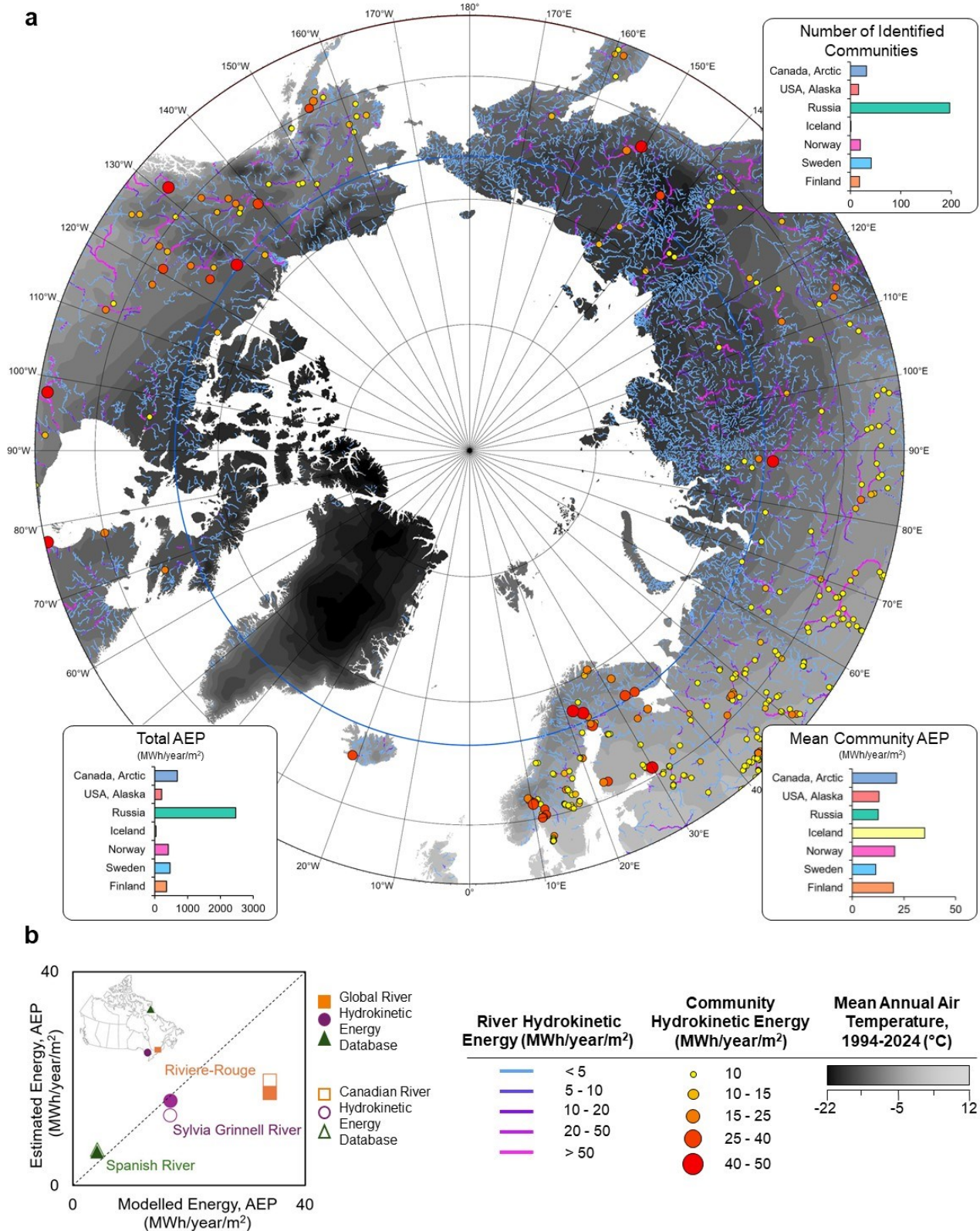


Figure 7-6: **Communities identified as feasible for HKE development in the global Arctic.** (a) Estimates of river HKE derived from global datasets, locations of

communities within 10 km of a river site with at least 10 MWh/year/m² estimated, and mean annual air temperature from daily temperature estimates in the 1994-2024 period. Also illustrated is the total AEP for all identified communities in each of the eight countries included in this analysis (Greenland excluded as no feasible communities were found), the total number of communities identified in each country, and the mean community AEP for each country. (b) Validation of the HKE estimates from the CRHE database and the global database at three locations where the AEP was modelled using field measurements and hydrodynamic models.

Russia had the highest total AEP at 2,470 MWh/year/m² across 197 communities, while Iceland had the lowest, with one community at 35 MWh/year/m². Country-level AEP totals and the number of identified communities are illustrated in Figure 7-6a. Despite its high total, Russia's average AEP per community (12.5 MWh/year/m²) was the second lowest, ahead of Sweden (11.3 MWh/year/m²). Iceland had the highest AEP per community (35.0 MWh/year/m²) for the one community identified as feasible. The next highest were Canada (21.4 MWh/year/m²), Norway (20.5 MWh/year/m²), and Finland (19.8 MWh/year/m²). Similar to the Canadian assessment, most feasible communities were located near river sites with sudden changes in river dimensions from local topography (e.g., bedrock width constrictions or steep mountain gradients) (Kirby et al., 2026).

The Arctic is warming faster than the global average, driving rapid changes in its hydrological cycle (McCrystall et al., 2021) with implications for HKE availability and distribution (Song et al., 2021). A transition from a snow- to rain-dominated regime, along with increased total precipitation, is expected (McCrystall et al., 2021). This shift will likely alter the shape and distribution of FDCs (Figure 7-2b) (Song et al., 2021), reducing melt-driven flows and increasing summer and fall precipitation (McCrystall et al., 2021). Historical data from the Eurasian Arctic indicate increased subsurface connectivity due to permafrost thaw, affecting rainfall-runoff dynamics and the mechanisms behind how rainfall is routed to rivers (Song et al., 2021). Concurrently, channel morphology may change as permafrost and ice, key factors in channel stability, diminish (Lauzon et al., 2019). River ice dynamics increase sediment movement both directly and by increasing vertical channel growth (Ettema, 2002; Lauzon et al., 2019); thus, it is expected that channels will become more mobile. These changes to precipitation, rainfall-runoff dynamics, and channel stability may both positively and negatively impact the magnitude and spatiotemporal distribution of HKE across the global Arctic.

7.3.4 Socioeconomic Realities for Hydrokinetic and Renewable Energy Development in the Arctic

The socio-economic landscape of hydrokinetic and RE development in the Arctic is shaped by community motivations, institutional constraints, and capacity limitations. Indigenous communities in the Arctic are often driven by the desire for energy autonomy,

resilience, reduced reliance on diesel, and cultural and environmental preservation. However, these motivations vary across communities, making universal solutions ineffective (Stefanelli et al., 2019).

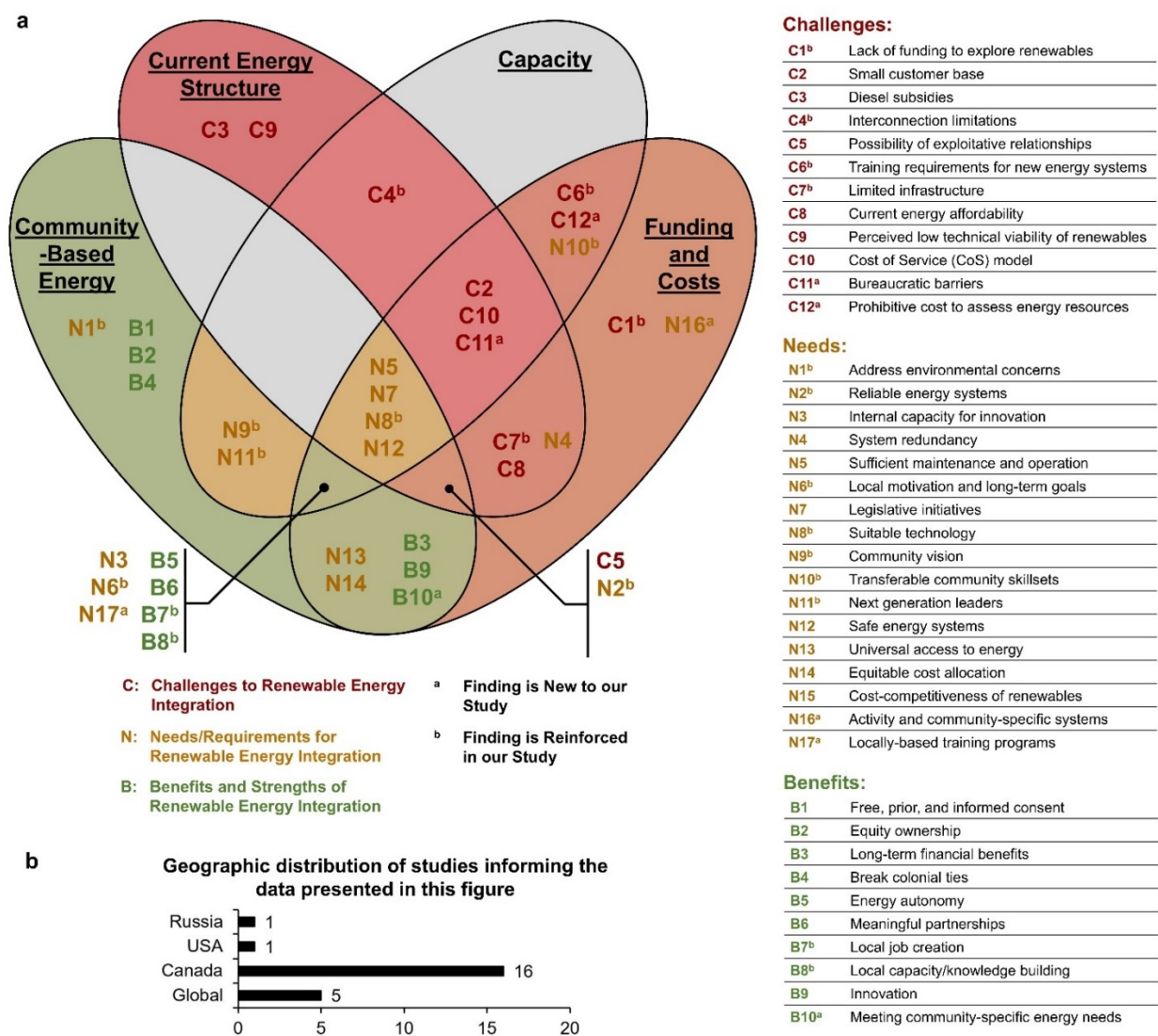


Figure 7-7: (a) **Barriers, needs, and benefits of renewable energy integration for Arctic communities**. This heat map four-way Venn diagram illustrates the complexity and interconnectivity of challenges that Arctic communities face to explore and implement renewable energy options, the potential solutions to these challenges and required framework for projects to be successful, and the benefits of RE projects to Arctic communities. Items with ^b have been reinforced by our study, and items with ^a are new findings from our study. These findings were collected as a part of this study as well as from these resources: (de Witt et al., 2021; Gritsenko and Salonen, 2021; He, 2023; Hoicka et al., 2021; Inuit Tapiriit Kanatami, 2018; Leonhardt et al., 2023, 2022; McCallum et al., 2021; McDonald and Pearce, 2013; McMaster et al., 2024; Nunavut

Arctic College, 2024; Nunavut Nukkiksautiit Corporation, 2023a, 2023b, 2023c; Pinard et al., 2023; Stefanelli et al., 2019; Weis et al., 2008; Yadav et al., 2023). This figure is not exclusive, and other factors that impact RE projects in the Arctic may not be included here, especially considering the possible bias towards Canada-based findings as shown in (b).

Figure 7-7a highlights the interconnected and complex challenges Arctic communities face in adopting RE, as well as the multifaceted conditions needed for success. Beyond cost savings and environmental benefits, RE can also enhance the social and cultural well-being of northern communities. This study and related literature suggest that four primary factors influence Arctic RE projects: funding and costs, capacity, the existing energy structure, and community-based energy. The heat map in Figure 7-7a illustrates how the current energy structure, costs, and capacity can hinder progress, but also how community-based initiatives can be leveraged alongside these elements to overcome barriers and advance RE adoption in Arctic communities.

Funding-related barriers and current energy systems are tightly related, which include high capital costs, limited financial support access, administrative delays, little to no financing opportunities, and structural disincentives under current utility revenue models (McDonald and Pearce, 2013; Weis et al., 2008). For instance, the Cost of Service (CoS) model in the Canadian North incentivizes consumption and asset ownership, discouraging efficiency and partnerships with independent RE producers (He, 2023). Even within this model, comparing RE to diesel is difficult because the true cost of heavily subsidized diesel in the Arctic remains uncertain. Until 2023, Nunavut's legislative framework also prohibited independent power producers, which excluded new entrants from the energy landscape. Communities face further competition for scarce funding resources (Leonhardt et al., 2022), while lengthy bureaucratic processes delay project approvals. The high cost of feasibility studies required for funding proposals create additional barriers. Even when projects move forward, diverse instruments, such as financial support, feed-in-tariffs, grid services, and fiscal incentives are essential for enabling RE development (Leonhardt et al., 2023, 2022).

Limited capacity can be a major barrier to RE development in the Arctic as well. The current socio-economic disparities present in some Arctic communities, like lower incomes and high food insecurity in Inuit Nunangat (Inuit Tapiriit Kanatami, 2018), and limited access to proper equipment and skilled labour limit capacity for RE development (Weis et al., 2008). Successful RE implementation requires socio-technical capacity in all project stages supported by seven pillars: local leadership, inter-community networks, long-term energy vision, value creation, energy literacy, transferable skills, and training opportunities (McMaster et al., 2024). This study emphasizes the importance of having a local, engaged community contact to push project progress. Relationship building and knowledge sharing were pivotal to project success. Furthermore, training local residents

has a great impact on project sustainability (McCallum et al., 2021) and facilitates job creation, a desire revealed in community interviews (Nunavut Arctic College, 2024).

Community-based energy systems are crucial for RE adoption in the Arctic. These systems involve understanding local capacity, local energy needs, social dynamics, and the long-term impacts of energy transitions (McMaster et al., 2024). Effective approaches include institutional reforms that promote Free, Prior, and Informed Consent (FPIC) (Nunavut Nukkiqsautiit Corporation, 2024), equity ownership (Hoicka et al., 2021) or other financial benefit sharing, and local education and engagement (Gritsenko and Salonen, 2021). Addressing common concerns, such as project ownership, functionality, funding, logistics, and environmental impacts, is essential (Nunavut Nukkiqsautiit Corporation, 2023a, 2023b, 2023c). In the case of HKE, interviewees raised specific concerns about fish health, caribou migration, biodiversity, and ice-related impacts on turbines (SevenGen Summit, 2024). Community-specific energy demand must be considered, as large grid-based systems may not suit small, dispersed Arctic settlements. Instead, micro-grids are often more appropriate (Uddin et al., 2023). In the Canadian Arctic, where widely spaced cabin-based dwellings support hunting and fishing, modular battery-based systems were identified as better suited to these local needs than large-scale grid integration.

Despite these challenges, many communities show readiness for RE adoption through existing strengths like local leadership, transferable skills, and emerging youth leaders (McMaster et al., 2024), and communities can still see benefits with externally initiated projects that bring new resources into the community (Gritsenko and Salonen, 2021).

7.4 Conclusions

Hydrokinetic energy (HKE) can offer a viable renewable energy alternative for remote Arctic communities that are heavily reliant on diesel fuel. Diesel reliance in Arctic communities poses environmental, economic, and logistical challenges, including high fuel costs, supply chain vulnerabilities, infrastructure deficits, and accelerated local climate impacts from black carbon emissions. The Iqaluit Kuunga River (Nunavut, Canada) case study demonstrated technical feasibility in one of the coldest Arctic regions, with the calculated energy yield comparable to an existing installation in Alaska that has been operating for two years and offsets community diesel usage by 60-90%.

Upon expanding the assessment nationally and globally, many communities were identified in the Arctic and sub-Arctic showing technical potential for HKE deployment, with 50 communities identified in Canada and 325 communities identified globally. A total theoretical maximum AEP of 1,770 MWh/year/m² was calculated for Canada, and the total global theoretical AEP was 4,626 MWh/year/m² for all identified communities. Diesel

offset was calculated for feasible Canadian communities with ten communities capable of 20% or more reduction in diesel with one turbine installation and fifteen communities capable of 5% or more reduction with one turbine. Russia exhibited the highest total AEP (2,470 MWh/year/m²) but a low average AEP per community (12.5 MWh/year/m²), while Iceland, Canada, Norway, and Finland had higher per-community average AEP, indicating that localized river characteristics are critical for favourable HKE conditions. Favourable HKE sites were typically associated with distinct topographic features such as bedrock constrictions and steep channel gradients.

Despite current socioeconomic barriers to RE development in the Arctic – including funding limitations, utility model disincentives, and capacity shortfalls – community-based energy systems, local leadership, and skill development are key enablers for successful renewable transitions. Community-based energy systems can benefit local communities beyond environmental impacts and cost-savings, and HKE shows promise as a community-based renewable energy alternative due to its minimal infrastructure footprint, low environmental impact, and relative ease of installation and maintenance compared to conventional hydropower.

Chapter 8. Findings, Interpretation, and Future Work

8.1 Summary of Key Findings

Key findings relating to site-specific and large-scale estimation of river HKE and distribution of river HKE resources nationally and globally based on the literature review (Chapter 2), site-specific river HKE estimation and analysis of turbine location (Chapter 3), optimization of data and methods to estimate river width from satellite imagery (Chapter 4 and Chapter 5), national river HKE estimates (Chapter 6), and river HKE estimates in the global Arctic (Chapter 7) are summarized as follows:

- The most feasible improvement to large-scale HKE resource estimation was improving channel width estimates from satellite imagery.
- The impact of seasonal flow variation, quantification of error, and utilization of hydrodynamic and hydrologic modelling techniques should always be considered in any type – site-specific or large-scale – of HKE assessment.
- Both seasonal and spatial variations in flow should be considered when estimating HKE resource at a river location.
- The velocity flow field should be incorporated into site-specific river HKE assessments by using a hydrodynamic model and spatially intense field data.
- Depending on the river site, the optimal turbine location may or may not change with flow condition.
- Surface water maps derived from S2MSI imagery were significantly more accurate than those derived from S1SAR imagery.
- It is justified to use S2MSI-derived surface water maps to validate S1SAR-derived surface water maps, despite the products' similar spatial resolution.
- No significant difference in surface water mapping accuracy was found between like- and cross-polarization as well as between dual and single polarization.
- The addition of the green band of multispectral imagery significantly improved the accuracy of surface water maps.
- For flooded landscapes, dual polarization out-performed other combinations of S1SAR polarizations and for images with river ice, cross-polarization performed best.
- The remote sensing surface water mapping method AWEI_NSH was found to be the overall most successful at accurately representing surface waterbodies.
- Neither spectral indices nor machine learning methods created more accurate surface water maps than the other.
- The newly developed Canadian river HKE database is able to identify localized areas of high energy potential due to changes in channel geometry. This database includes 288,000 km of streamlines with an average of 190 m between cross-

sectional estimates and a total of 1,325,261 river cross sections measured (Kirby et al., 2025b).

- High HKE locations were found in British Columbia, Eastern Ontario, Quebec, and Eastern Manitoba where significant topographic variations existed.
- The most promising locations for HKE development were the Pacific, Maritimes, Nelson, and St. Lawrence drainage basins, in order of resource potential.
- Validation of the Canadian river HKE database confirmed good agreement between database estimates and both field-measured and modelled values, with indications that improvements to the estimation of river depth would have the greatest improvement in future HKE estimates.
- The case study of an Arctic river, Iqaluit Kuunga River, illustrated that HKE may be feasible for remote Arctic communities.
- 50 remote communities in Canada were found to be feasible for HKE turbine deployment with ten communities able to achieve 20% diesel offset with a single turbine and fifteen communities able to achieve 5% diesel offset with one turbine.
- 325 communities were identified in the Global Arctic to be feasible for HKE resource extraction, with Russia containing the highest number of feasible communities (197), but the lowest mean AEP per community (12.5 MWh/year/m²).
- The countries with the highest mean AEP per community were Iceland (35.0 MWh/year/m²; 1 community), Canada (21.4 MWh/year/m²; 31 communities), and Norway (20.5 MWh/year/m²; 20 communities).
- The main thematic categories identified as most important to renewable energy transition in remote Arctic communities were: funding and costs, capacity, current energy structure, and community-based energy systems.

8.2 Synthesis and Discussion

This section explores how the various chapters in this thesis relate to each other, not included thus far within the individual chapters. The synthesis of the individual findings into combined insights provides understanding into future needed areas of research, appropriate use cases for the data generated in this work, and to illustrate the general advancement in the field of HKE estimation presented in this thesis.

- Rather than generating a single value of river width at mean annual flow from remote sensing, it is now possible to systematically generate multiple measurements of river width at cross-sections across different flow conditions (Ch. 4, 5). This is enabled by advances in cloud computing and automated GIS techniques to process large amounts of medium-resolution satellite imagery (Ch. 6). Thus, with the recommended inclusion of this advancement in future iterations of the Global Arctic HKE database, velocity and HKE estimates will become more accurate, especially at low and high flow conditions (Ch. 7).

- New methods were developed to obtain river width measurements from satellite imagery to improve the CRHE database (Ch. 4, 5). These methods included (1) the systematic processing of satellite imagery, divided by different seasonal periods, to derive nation-wide surface water maps for each seasonal period using cloud computing and (2) the automation of GIS tools to derive and quality check seasonal river width measurements from the national surface water maps (Ch. 6).
- The validation of field data-derived estimates of HKE and estimates of HKE in the CRHE and Global Arctic HKE databases illustrated the appropriate use cases for the large-scale datasets. Although the AEP value agreed well at the three validation locations for both the CRHE and Global Arctic HKE datasets, validation of velocity and power across flow exceedances at both the field sites (Ch. 3, 7) and the gauge locations (Ch. 6) illustrated that relying on the databases for estimates of velocity or power at a particular flow condition are less accurate. Thus, the appropriate use case for the CRHE and Global Arctic HKE datasets (Ch. 6, 7) is for site pre-reconnaissance and cannot replace full HKE assessments outlined by IEC (2019) and performed in this work.
- Improvements to river depth estimation beyond the use of hydraulic geometry principles was identified as a crucial requirement to the improved large-scale estimation of HKE in the literature review (Ch. 2). This need was further demonstrated in the validation of CRHE database (Ch. 6). A notable portion of error in the CRHE database HKE estimates was attributed to the method used to estimate river depth, and these depth errors can also be assumed to influence HKE errors in the Global Arctic HKE dataset (Ch. 7). Recent promising methods of improving river depth estimates, such as the application of green LiDAR to measure depth (Sundt et al., 2021) which is currently limited by the water clarity (Secchi depth) of the studied waterbody (Kastdalen et al., 2024), are recommended to be evaluated for large-scale river depth estimation feasibility.
- Spatial resolution between site-scale (Ch. 3, 7) and large-scale (Ch. 5, 7) illustrates that even within the fine resolution of the large-scale estimates (mean 190m) that higher energy locations can exist if localized high energy conditions are present due to sudden changes in channel geometry.
- Seasonal flow variability must be explicitly represented in large-scale databases (Ch. 6, 7), consistent with the site-scale analyses (Ch. 3, 7). Under- or over-prediction of velocity and HKE can occur when an insufficient range of flow conditions is included, particularly if estimates are derived only at mean annual flow (including associated width and depth). Reliance on a single representative discharge does not adequately capture variability across the full flow duration curve (FDC). IEC (2019) recommends a 15-point FDC; this work applied a 17-point FDC to better resolve flow variability. Future database development should prioritize inclusion of a sufficient number of flow conditions to robustly represent the full FDC and reduce bias in large-scale HKE estimates; however, a fewer number of flows may be sufficient if the selected set of flows adequately captures the full variability of the FDC (Kirby et al., 2022b).

- A clear distinction in the dominant sources of uncertainty is evident across assessment scales. At the site scale (Ch 3, 7), uncertainty is primarily driven by hydrodynamic model error and field measurement error, typically on the order of 10–20%. At the national scale (Ch. 6), is generally greater than that of site-based estimates. Sensitivity analyses indicate that flow ($R^2 = 0.81$) and depth ($R^2 = 0.63$) estimates exert the strongest control on HKE uncertainty, with depth contributing most substantially. Additional sources of bias include limitations in remotely sensed river width estimation, despite strong agreement ($R^2 = 0.95$), a slight positive bias is introduced by threshold selection that may classify shoreline pixels as water (Ch. 4, 5), as well as assumptions embedded in hydraulic geometry relationships. These relationships are limited to unregulated rivers and are influenced by the spatial distribution of WSC hydrometric stations, which propagates bias into both national and global databases. At the global scale, uncertainty is also generally greater relative to site measurements (Ch. 7). Depth is again likely the dominant source of uncertainty due to reliance on hydraulic geometry assumptions, although the individual influence of width and flow has not been evaluated as extensively compared to the national database. Across all scales, river ice introduces additional uncertainty by affecting both turbine operability and flow velocity (Ch. 3, 6, 7). These uncertainties propagate directly into AEP estimates and influence interpretation of results. While the databases are appropriate for estimating relative AEP and river width, velocity, flow, and depth values should be treated cautiously and verified locally where possible.

8.3 Limitations and Recommendations for Further Research

The limitations of the data and methods used to estimate national and global Arctic river HKE, as well as the site-specific estimations of river HKE, presented in this thesis are discussed at length in Chapter 3, Chapter 4, Chapter 5, Chapter 6, and Chapter 7. Key limitations are summarized as follows:

- The lack of ability to estimate of channel depth from remote sensing remains a limitation.
- Practical considerations for turbine deployment feasibility were not considered in the site-specific assessments, such as other uses of the river location, local climatic conditions, turbine depth requirements, or approximate cost of energy.
- The comparison of remotely sensed data for surface water mapping was limited by the data available in the region and if more polarizations were available, the analysis could have been expanded.
- Sensitivity testing of the training/testing ratio for surface water mapping machine learning methods was not performed and the ratio was statically set at 50/50.

- Spectral index methods to map surface water were not tested at the same location in different seasonal conditions (i.e., multiple images per area).
- Advanced machine learning methods (e.g., deep learning), combined methods, and thorough hyperparameter optimization were not explored for optimization of extracting river width measurements from satellite imagery.
- Locations with narrower rivers and/or persistent cloud and snow cover had fewer useable satellite-based river width measurements.
- In the validation of the Canadian HKE database, river depth estimation emerged as a primary source of error in the velocity and energy calculations.
- Following validation of the Canadian HKE database, flow estimates used in the calculation of HKE were found to contain more error in particular geographic areas, such as prairie regions with complex hydrology.
- The Canadian HKE database does not take into account proximity to electrical grids, ice and other practical engineering challenges, or ecological impacts of the turbines.
- As a similar approach used in the Canadian HKE database was employed to estimate river depths in the Global Arctic database, river depth estimates were similarly a main source of error for HKE estimates.
- Validation of Global Arctic HKE resource estimates was not performed outside of Canadian locations.
- The analysis of energy transition readiness for remote Arctic communities was performed with a Canadian bias, with 16 of the 23 published cited literature sources having a Canadian context.

Opportunities for further research on site-specific and large-scale river HKE resource estimation are also identified within Chapter 3, Chapter 4, Chapter 5, Chapter 6, and Chapter 7, and are summarized as follows:

- Newly available methods of developing complex data-driven regression relationships using machine learning should be explored for river depth estimation.
- As LiDAR-based DEMs become available, updated methods to estimate depth and velocity may improve HKE estimates.
- IEC standards for river HKE assessments should be further reviewed for the possibility of being prohibitive to resource estimation and development.
- Drone-based surface image velocimetry should be explored for use in site-scale HKE resource analysis to improve accessibility and safety.
- The dual polarizations HH/VV or VV/HV should be tested to compare the accuracy of derived surface water maps.
- The greatest improvement to the Canadian HKE database would be achieved upon improving estimates of river depth and flow.
- For sites identified as promising in the Canadian or Global HKE datasets, detailed resource estimation should be performed, including numerical modelling of river

hydraulics and associated ecological impacts, ice impact studies, and energy transition readiness studies focusing on local factors.

- Inclusion of improved depth and flow estimations as well as including multiple width measurements at different seasonal conditions would increase the accuracy of river HKE estimates in the Global Arctic database.
- Validation of the Global Arctic HKE database at locations outside of Canada should be performed in the future when data becomes available.
- Inclusion of climate change estimates to river flow values should be performed in the future to understand possible changing trends in HKE availability.
- The impact of turbine deployment on flow and sediment transport should be performed using numerical modelling for natural channel sites, rather than using flumes or dam tailraces with simplified channel geometry as study areas.
- To develop a more complete understanding of energy transition readiness for remote Arctic communities, further study should be conducted to provide Global information outside of Canadian only context.

Chapter 9. Conclusion

A novel comprehensive literature review related to site-specific and large-scale river HKE estimation, a site-specific assessment of river HKE and turbine location optimization, data and method optimization in river width estimation for large-scale HKE assessments, development of national and global Arctic river HKE estimates, and analysis of the socioeconomic and practical challenges and enabling conditions for renewable energy in the Arctic were used to provide a comprehensive examination of the feasibility of river HKE extraction in northern locations, particularly for remote northern communities. Using these resources, remote communities feasible for HKE transition in the Canadian and Global Arctic were identified and possible diesel fuel offset was calculated for remote Canadian communities. Future improvements for site-specific and large-scale HKE resource assessments were identified and recommended; specifically, improved river depth and flow estimates could increase accuracy of velocity and power estimates. Recommendations were provided to improve site-specific resource assessments of river HKE – specifically the inclusion of the seasonal flow variance and the spatial variance in velocity across the study domain – illustrating limitations in previous resource assessment studies. In addition to the technical river energy resource, the socioeconomic barriers and enabling conditions for renewable energy transition were found to lie in four thematic categories (funding and costs, capacity, current energy structure, and community-based energy), and community-based energy systems considering local factors were identified to be most promising for remote northern communities.

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Appendix A. Supplementary Material for Chapter 5:

Optimization of Surface Water Mapping Methods

Table A-1. Landcover characteristics of the study locations based on the Landcover of Canada dataset (Canada Centre for Remote Sensing; Natural Resources Canada; Government of Canada, 2015)

Landcover class	Landcover Description	Red River	Sylvia Grinnell River	Rivière-Rouge	Fraser River
1	Temperate or sub-polar needleleaf forest	-	-	1.7%	36.2%
5	Temperate or sub-polar broadleaf deciduous forest	6.4%	-	34.3%	0.02%
6	Mixed forest	-	-	15.5%	0.03%
8	Temperate or sub-polar shrubland	0.6%	-	2.8%	1.0%
10	Temperate or sub-polar grassland	1.8%	-	0.5%	34.3%
11	Sub-polar or polar shrubland–lichen–moss	-	0.3%	-	-
12	Sub-polar or polar grassland–lichen–moss	-	12.8%	-	0.01%
13	Sub-polar or polar barren–lichen–moss	-	68.2%	-	-
14	Wetland	1.9%	-	0.3%	-
15	Cropland	76.3%	-	11.3%	1.5%
16	Barren land	0.04%	1.8%	1.7%	15.9%
17	Urban and built-up	5.5%	10.8%	5.8%	6.2%
18	Water	7.5%	6.1%	26.2%	4.9%
19	Snow and ice	-	0.03%	-	-

Table A-2. NDWI threshold sensitivity testing, optimized threshold CSI highlighted for each location

Location		Threshold:					
(Water Area)	Metric	-0.3	-0.2	-0.1	0	0.1	0.2
Red River (2.34 km ²)	MA*	1.96 (84.0%)	1.88 (80.6%)	1.80 (77.2%)	1.71 (73.1%)	1.58 (67.6%)	-
	OE	0.37	0.45	0.53	0.62	0.75	-
	CE	0.97	0.23	0.04	0.01	0.00	-
	CSI	59.4%	73.4%	76.0%	73.1%	67.6%	-
Sylvia Grinnell River (2.11 km ²)	MA*	1.67 (79.1%)	1.59 (75.2%)	1.50 (71.2%)	1.39 (65.9%)	1.29 (61.4%)	-
	OE	0.43	0.52	0.61	0.72	0.81	-
	CE	4.08	2.74	1.11	0.12	0.03	-
	CSI	27.0%	32.8%	46.6%	62.4%	60.6%	-
Rivière-Rouge (5.18 km ²)	MA*	4.90 (94.7%)	4.80 (92.7%)	4.64 (89.6%)	4.41 (85.2%)	4.12 (79.5%)	-
	OE	0.27	0.38	0.54	0.77	1.06	-
	CE	0.36	0.19	0.02	0.01	0.00	-
	CSI	88.7%	89.5%	89.3%	85.1%	79.5%	-
Fraser River (1.15 km ²)	MA*	1.15 (99.7%)	1.14 (99.1%)	1.14 (99.0%)	1.12 (97.5%)	1.08 (93.9%)	1.03 (89.4%)
	OE	0.00	0.01	0.01	0.03	0.06	0.12
	CE	3.90	1.38	0.31	0.10	0.06	0.03
	CSI	22.7%	45.2%	77.9%	89.7%	90.3%	87.4%

Table A-3. MNDWI threshold and resampling sensitivity testing, optimized threshold CSI highlighted for each location

Location		Threshold:					
(Water Area)	Metric	-0.3	-0.2	-0.1	0	0.1	0.2
No Resampling							
Red River (2.34 km²)	MA*	2.07 (88.4%)	1.97 (84.4%)	1.87 (80.2%)	1.78 (76.2%)	1.66 (71.0%)	-
	OE	0.27	0.37	0.46	0.56	0.67	-
	CE	1.07	0.31	0.16	0.1	0.07	-
	CSI	60.8%	74.5%	75.0%	73.2%	69.2%	-
Sylvia Grinnell River (2.11 km²)	MA*	1.18 (56.0%)	1.03 (49.1%)	0.91 (43.2%)	0.79 (37.4%)	0.69 (32.6%)	-
	OE	0.92	1.07	1.19	1.32	1.41	-
	CE	2.49	0.95	0.25	0.11	0.10	-
	CSI	25.8%	33.9%	38.7%	35.5%	31.3%	-
Rivière-Rouge (5.18 km²)	MA*	5.00 (96.5%)	4.91 (94.8%)	4.78 (92.3%)	4.65 (89.8%)	4.52 (87.3%)	-
	OE	0.18	0.27	0.40	0.53	0.66	-
	CE	0.60	0.22	0.09	0.04	0.02	-
	CSI	86.5%	90.9%	90.7%	89.1%	86.9%	-
Fraser River (1.15 km²)	MA*	1.12 (97.0%)	1.10 (95.9%)	1.07 (92.9%)	1.04 (90.5%)	1.00 (86.9%)	-
	OE	0.03	0.05	0.08	0.11	0.15	-
	CE	1.67	0.55	0.22	0.13	0.10	-
	CSI	39.5%	65.0%	78.0%	81.4%	79.7%	-
Resampled							
Red River (2.34 km²)	MA*	2.16 (92.2%)	2.04 (87.5%)	1.93 (82.8%)	1.82 (78.1%)	1.67 (71.3%)	-
	OE	0.18	0.29	0.40	0.51	0.67	-
	CE	0.99	0.25	0.10	0.04	0.01	-
	CSI	65.0%	79.1%	79.5%	76.6%	71.0%	-
Sylvia Grinnell River (2.11 km²)	MA*	1.15 (54.6%)	1.04 (49.5%)	0.92 (43.7%)	0.79 (37.8%)	0.69 (32.5%)	-
	OE	0.95	1.06	1.18	1.31	1.42	-
	CE	2.50	1.01	0.29	0.13	0.09	-
	CSI	25.0%	33.5%	38.4%	35.6%	31.3%	-
Rivière-Rouge (5.18 km²)	MA*	4.97 (96.0%)	4.88 (94.2%)	4.76 (91.9%)	4.63 (89.5%)	4.50 (86.8%)	-
	OE	0.20	0.29	0.42	0.55	0.68	-
	CE	0.57	0.25	0.10	0.05	0.02	-
	CSI	86.5%	90.3%	90.1%	88.7%	86.5%	-
Fraser River (1.15 km²)	MA*	1.14 (99.0%)	1.13 (98.3%)	1.12 (97.2%)	1.09 (95.3%)	1.06 (92.3%)	1.02 (88.6%)
	OE	0.01	0.02	0.03	0.05	0.09	0.13
	CE	1.67	0.59	0.22	0.10	0.05	0.03
	CSI	40.4%	65.0%	81.8%	87.8%	88.1%	86.1%

Table A-4. AWEI_SH threshold and resampling sensitivity testing, optimized threshold CSI highlighted for each location

Location		Threshold:				
(Water Area)	Metric	-0.3	-0.2	-0.1	0	0.1
No Resampling						
Red River (2.34 km ²)	MA*	2.23 (95.4%)	2.15 (91.9%)	2.01 (85.9%)	1.67 (71.5%)	-
	OE	0.10	0.18	0.33	0.66	-
	CE	0.40	0.17	0.07	0.02	-
	CSI	81.8%	85.9%	83.4%	70.9%	-
Sylvia Grinnell River (2.11 km ²)	MA*	1.84 (87.1%)	1.68 (79.6%)	1.47 (69.4%)	0.98 (46.7%)	-
	OE	0.26	0.42	0.64	1.12	-
	CE	3.51	2.00	0.87	0.13	-
	CSI	32.7%	40.9%	49.3%	44.0%	-
Rivière-Rouge (5.18 km ²)	MA*	5.14 (99.2%)	5.10 (98.4%)	5.00 (96.5%)	4.58 (88.4%)	-
	OE	0.04	0.08	0.18	0.60	-
	CE	1.45	0.46	0.15	0.01	-
	CSI	77.6%	90.5%	93.9%	88.2%	-
Fraser River (1.15 km ²)	MA*	-	1.14 (98.8%)	1.11 (96.3%)	1.06 (91.9%)	0.97 (84.0%)
	OE	-	0.01	0.04	0.09	0.18
	CE	-	1.82	0.45	0.12	0.06
	CSI	-	38.3%	69.4%	83.4%	80.2%
Resampled						
Red River (2.34 km ²)	MA*	2.24 (95.7%)	2.16 (92.4%)	2.03 (86.5%)	1.71 (73.0%)	-
	OE	0.10	0.17	0.31	0.63	-
	CE	0.45	0.18	0.07	0.02	-
	CSI	80.5%	86.0%	84.2%	72.5%	-
Sylvia Grinnell River (2.11 km ²)	MA*	1.86 (88.0%)	1.70 (80.4%)	1.47 (69.6%)	0.98 (46.6%)	-
	OE	0.25	0.41	0.63	1.12	-
	CE	3.50	1.99	0.85	0.16	-
	CSI	33.1%	41.5%	49.8%	43.4%	-
Rivière-Rouge (5.18 km ²)	MA*	5.12 (98.8%)	5.07 (97.9%)	4.97 (95.9%)	4.57 (88.3%)	-
	OE	0.06	0.10	0.21	0.60	-
	CE	1.51	0.50	0.16	0.02	-
	CSI	76.5%	89.4%	93.0%	88.1%	-
Fraser River (1.15 km ²)	MA*	-	1.15 (99.8%)	1.14 (99.1%)	1.10 (95.7%)	-
	OE	-	0.00	0.01	0.05	-
	CE	-	1.80	0.43	0.09	-
	CSI	-	38.9%	72.2%	88.5%	-

Table A-5. AWEI_NSH threshold and resampling sensitivity testing, optimized threshold
CSI highlighted for each location

Location		Threshold:					
(Water Area)	Metric	-0.5	-0.4	-0.3	-0.2	-0.1	0
No Resampling							
Red River (2.34 km²)	MA*	2.18 (93.2%)	2.10 (89.8%)	2.02 (86.2%)	1.92 (82.2%)	1.79 (76.5%)	1.48 (63.4%)
	OE	0.15	0.23	0.32	0.41	0.54	0.85
	CE	0.40	0.29	0.20	0.12	0.06	0.01
	CSI	79.8%	80.2%	79.7%	78.2%	74.8%	63.0%
Sylvia Grinnell River (2.11 km²)	MA*	1.56 (74.2%)	1.45 (68.8%)	1.31 (62.3%)	1.16 (54.8%)	0.93 (44.3%)	0.49 (23.5%)
	OE	0.54	0.65	0.79	0.95	1.17	1.61
	CE	0.49	0.23	0.15	0.10	0.07	0.04
	CSI	60.3%	62.2%	58.4%	52.5%	43.0%	23.1%
Rivière-Rouge (5.18 km²)	MA*	-	5.11 (98.7%)	5.06 (97.8%)	4.97 (95.9%)	4.78 (92.2%)	4.36 (84.3%)
	OE	-	0.06	0.11	0.21	0.40	0.81
	CE	-	1.06	0.46	0.21	0.07	0.01
	CSI	-	82.0%	89.9%	92.2%	91.1%	84.2%
Fraser River (1.15 km²)	MA*	-	-	1.06 (92.5%)	1.04 (90.1%)	0.99 (86.5%)	0.95 (82.2%)
	OE	-	-	0.09	0.11	0.16	0.20
	CE	-	-	0.98	0.35	0.13	0.07
	CSI	-	-	49.9%	69.0%	77.8%	77.7%
Resampled							
Red River (2.34 km²)	MA*	2.24 (95.7%)	2.17 (92.7%)	2.08 (89.0%)	1.97 (84.0%)	1.805462885	1.51 (64.7%)
	OE	0.10	0.17	0.25	0.37	0.53	0.83
	CE	0.38	0.24	0.14	0.07	0.02	0.01
	CSI	82.4%	84.3%	84.0%	81.8%	76.6%	64.5%
Sylvia Grinnell River (2.11 km²)	MA*	1.57 (74.3%)	1.44 (68.4%)	1.30 (61.4%)	1.13 (53.5%)	0.91 (43.4%)	0.53 (25.2%)
	OE	0.54	0.66	0.81	0.97	1.19	1.57
	CE	0.44	0.20	0.12	0.08	0.06	0.05
	CSI	61.7%	62.7%	58.3%	51.6%	42.3%	24.8%
Rivière-Rouge (5.18 km²)	MA*	-	5.08 (98.1%)	5.03 (97.0%)	4.93 (95.2%)	4.76 (91.8%)	4.35 (84.1%)
	OE	-	0.10	0.15	0.25	0.42	0.82
	CE	-	1.10	0.48	0.22	0.07	0.01
	CSI	-	81.0%	88.8%	91.3%	90.7%	84.0%
Fraser River (1.15 km²)	MA*	-	-	1.12 (97.0%)	1.09 (95.0%)	1.05 (91.7%)	1.00 (86.6%)
	OE	-	-	0.03	0.06	0.10	0.15
	CE	-	-	0.92	0.30	0.07	0.03
	CSI	-	-	54.0%	75.2%	86.1%	84.5%

Table A-6. AWEI_BOTH threshold and resampling sensitivity testing, optimized threshold CSI highlighted for each location

Location		Threshold:					
(Water Area)	Metric	-0.3	-0.2	-0.1	0	0.1	Combination*
No Resampling							
Red River (2.34 km²)	MA*	2.22 (94.8%)	2.14 (91.4%)	2.04 (87.4%)	1.71 (73.4%)	-	-
	OE	0.12	0.20	0.29	0.62	-	-
	CE	0.52	0.25	0.10	0.04	-	-
	CSI	77.6%	82.9%	83.8%	72.3%	-	-
Sylvia Grinnell River (2.11 km²)	MA*	1.84 (87.1%)	1.68 (79.6%)	1.45 (68.8%)	0.99 (46.8%)	-	-
	OE	0.26	0.42	0.65	1.12	-	-
	CE	3.51	2.00	0.82	0.17	-	-
	CSI	32.7%	40.9%	49.6%	43.4%	-	-
Rivière-Rouge (5.18 km²)	MA*	5.13 (99.1%)	5.10 (98.4%)	5.00 (96.4%)	4.59 (88.7%)	-	5.03 (97.0%)
	OE	0.04	0.08	0.18	0.58	-	0.15
	CE	1.55	0.49	0.16	0.02	-	0.25
	CSI	76.3%	89.9%	93.5%	88.3%	-	92.7%
Fraser River (1.15 km²)	MA*	1.15 (99.6%)	1.14 (98.8%)	1.11 (96.8%)	1.06 (92.1%)	-	-
	OE	0.00	0.01	0.04	0.09	-	-
	CE	5.75	1.82	0.40	0.12	-	-
	CSI	16.6%	38.2%	71.9%	83.5%	-	-
Resampled							
Red River (2.34 km²)	MA*	2.24 (95.7%)	2.16 (92.5%)	2.04 (87.5%)	1.74 (74.5%)	-	2.24 (95.7%)
	OE	0.09	0.17	0.29	0.60	-	0.09
	CE	0.45	0.18	0.07	0.02	-	0.45
	CSI	80.4%	86.0%	85.1%	73.9%	-	80.4%
Sylvia Grinnell River (2.11 km²)	MA*	1.86 (88.0%)	1.70 (80.4%)	1.46 (69.5%)	1.00 (47.3)	-	1.50 (71.0%)
	OE	0.25	0.41	0.64	1.11	-	0.60
	CE	3.50	1.99	0.78	0.14	-	0.86
	CSI	33.1%	41.5%	50.7%	44.3%	-	50.7%
Rivière-Rouge (5.18 km²)	MA*	5.12 (98.8%)	5.07 (97.9%)	4.97 (95.9%)	4.59 (88.6%)	-	-
	OE	0.06	0.10	0.21	0.59	-	-
	CE	1.52	0.50	0.17	0.01	-	-
	CSI	76.4%	89.4%	92.9%	88.4%	-	-
Fraser River (1.15 km²)	MA*	1.15 (99.9%)	1.15 (99.8%)	1.14 (99.1%)	1.10 (96.1%)	1.01 (88.0%)	1.10 (95.9%)
	OE	0.00	0.00	0.01	0.04	0.14	0.05
	CE	5.77	1.80	0.43	0.09	0.03	0.12
	CSI	16.6%	38.9%	72.2%	89.2%	86.1%	87.0%

*Combination of the optimized thresholds of each AWEI spectral index, as follows with SH threshold first and NSH threshold second: (RedR) -0.2, -0.4; (SGR) -0.4, -0.1; (RougeR) -0.2, -0.1; (FR) -0.1, 0.

Table A-7. Acronyms of LWIC methods in other comparison studies in Table 5-6

Study	Acronym	Definition
Alcaras et al.	RGR	Red-Green Ratio Index
	NDVI	Normalized Difference Vegetation Index
	EVI	Enhanced Vegetation Index
	NRR	NIR-Red Ratio Index
Aroma and Raimond	FCM	Fuzzy C Means
	ARKFCM	Adaptive Regularized Kernel Fuzzy C Means
	SLIC	Simple Linear Iterative Clustering-Based Superpixel Segmentation
Dona et al.	GP	Genetic Programming
	ANN	Artificial Neural Network
	I_CEDX	Index proposed by Angel-Martinez
	SAVI	Soil-Adjusted Vegetation Index
Pena-Reguerio	RE-NDWI	NDWI but with Band 5 instead of Band 8 NIR (Sentinel-2)
	B_BLUE	NDWI but with Blue Band instead of Green Band
Zhang et al.	CIWI	Combined Index of NDVI and NIR
Hafiza Wajiha Khalid et al.	NDMI	Normalized Difference Moisture Index
	NWI	New Water Index
	LBWEI	LST-Based Water Extraction Index
Ireland et al.	rkFDA	Regularized Kernel Fisher's Discriminant Analysis
	RBF	Gaussian Radial Basis Function
Senel et al.	TCWI	Tasseled Cap Wetness Index
Feizizadeh et al.	CART	Classification and Regression Tree
Otukei and Blaschke	DT	Decision Tree
Thati et al.	ISODATA	Iterative Self-Organizing Data Analysis

Appendix B. Hydrokinetic Energy Analysis

Community Pamphlets

River Hydrokinetic Energy Resource Estimated near Sagamok



In collaboration with Natural Resources Canada and National Research Council Canada.
This work was approved by the Science Committee of Sagamok First Nation.

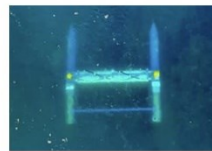
Hydrokinetic energy facts:

- The higher the river speed, the more hydrokinetic energy that can be extracted.
- Hydrokinetic power has less impact on fish and sediment/nutrient transport compared to traditional hydropower.
- The amount of carbon from a hydrokinetic turbine's operations, installation, and maintenance is estimated to be only 1.3% of the diesel-based carbon.

Example of a Hydrokinetic Turbine

ORPC RivGen:

- Igiugig, Alaska
- Operates during winter
- 40 kW



DATA COLLECTION

Method of Collecting Data

- Equipment mounted on motor boat to collect data on the river



Survey Approach

1. Identify promising locations for hydrokinetic energy
2. Collect data across river



Equipment Used

Acoustic Doppler Current Profiler (ADCP)

Uses sounds to measure:

- Speed and direction of water movement
- Height of water
- Distance to bottom



RTK-GPS

- Improves positional accuracy of ADCP data

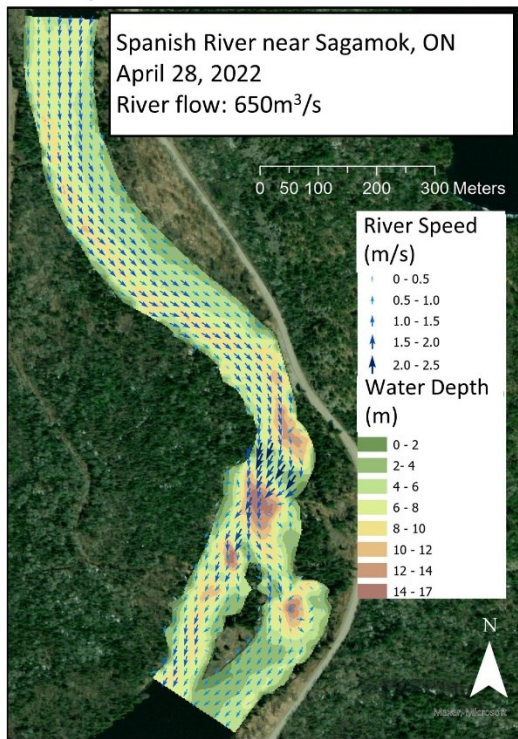


RESULTS

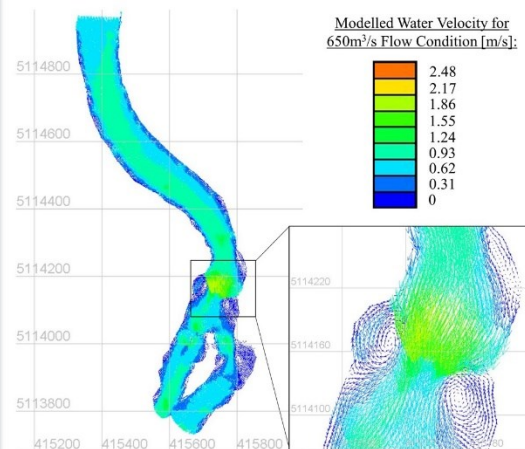
The outcome of the research is data and information that has been transferred to the community. The community will maintain data ownership.

Map of River Area

- River depth
- Speed and direction of water



The Most Promising Location is Located at the Riverbend



- Flow is sped up here by a bedrock formation
- It was also observed to be a popular fishing spot

The Amount of River Hydrokinetic Energy Resource in the Spanish River

Extracting hydrokinetic energy from the Spanish River is likely **not feasible** near Sagamok

With an assumed power coefficient of 0.45, an average **1.35 MWh/year** of power is expected to be produced with a 1m² turbine

Typical values for a feasible site are **5+ MWh/year**

Project Researchers



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Email: [REDACTED]



Katelyn Kirby, Ph.D. Candidate

Email: [REDACTED]

The full study results can be found in "Spanish River Hydrokinetic Energy Resource Assessment Report", July 2023.

Figure B-1: Hydrokinetic energy analysis of the Spanish River pamphlet for the Sagamok First Nation Community.

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 ለጥንቃቄው ለጥንቃቄው ለጥንቃቄው

$\Delta d^L L^{\text{qb}} d n c \triangleright \tau^a a^{\text{c}} \sigma^{\text{q}} L L^c \sigma^{\text{b}} \triangleright \tau^{\text{b}}$
 $\tau^{\text{b}} m \Delta^c \triangleright \sigma^{\text{q}} L \sigma^c \triangleleft \tau n^{\text{q}} L. \triangleleft^{\text{q}} \tau \sigma^{\text{b}} \text{h} \Delta^c$
 $\triangleleft \triangleright \hat{n}^c \Delta d^L L^{\text{qb}} d n c \triangleright \tau^a a^{\text{c}} \sigma^{\text{b}} \text{h} \Delta^c.$

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River Hydrokinetic Energy Resource Estimated on the Sylvia Grinnell River

In collaboration with Qikiqtaaluk Corporation and Nunavut Nukkiqsautiit Corporation (NNC).
This work has been approved by the Nunavut Research Institute.



Hydrokinetic (hydro = water, kinetic = speed) energy facts:

- The higher the **river speed**, the more **hydrokinetic energy** that can be extracted.
- Hydrokinetic power has **less impact** on fish and sediment/nutrient transport compared to traditional hydropower.
- The amount of **carbon** from a hydrokinetic turbine's operations, installation, and maintenance is estimated to be only **1.3%** of the diesel-based carbon.

Example of a Hydrokinetic Turbine

ORPC RivGen (40 kW):

- Igiugig, Alaska
- Offset community diesel use by 50%
- Community led & operated



DATA COLLECTION

Method of Collecting Data

- Battery-powered remote-controlled boat



Study Location



Equipment Used

Acoustic Doppler Current Profiler (ADCP)

Uses sound to measure:

- Speed and direction of water movement
- Height of water
- Distance to river bottom



RTK-GPS

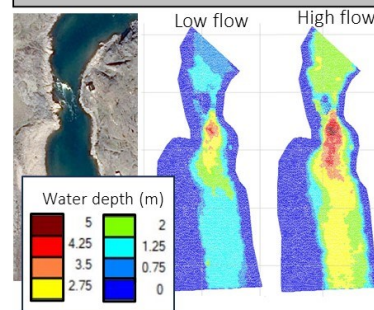
- Improves positional accuracy of ADCP data



RESULTS

The outcome of the research is data and information that has been transferred to the community (HTO & NCC). The community will maintain data ownership.

Measured water depth

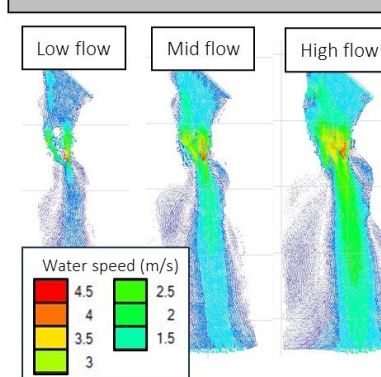


The Most Promising Location is Located Downstream of Rapids

Flow is sped up here by the rock formation.

High speed is expected throughout the open water season.

Power across different seasons



The Amount of River Hydrokinetic Energy Resource in the Sylvia Grinnell River

Extracting hydrokinetic energy from the Sylvia Grinnell River north of Iqaluit is likely **feasible** in **open water** conditions (turbine removed in winter).

An average **75 MWh/year** of power is expected to be produced with one 10m² turbine. This could potentially power 13 houses with 1 turbine.

The power produced depends on the turbine. Larger turbines produce more power.

For more information, please contact:



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All study data can be found in the file "SylviaGrinnell_Hydrokinetic_Data.zip", Sept 2024.

Figure B-3: Hydrokinetic energy analysis of the Iqaluit Kuunga (Sylvia Grinnell) River pamphlet for Iqaluit, Nunavut and Amaruq Hunters and Trappers Association (in English).